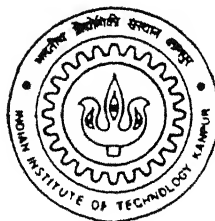


# MULTI-OBJECTIVE OPTIMISATION OF INJECTION MOLDING PROCESS PARAMETERS: A STUDY USING GENETIC ALGORITHMS

by

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DEPARTMENT OF INDUSTRIAL AND MANAGEMENT ENGINEERING  
**INDIAN INSTITUTE OF TECHNOLOGY KANPUR**

February, 1999

# **MULTI-OBJECTIVE OPTIMISATION OF INJECTION MOLDING PROCESS PARAMETERS : A STUDY USING GENETIC ALGORITHMS**

**A Thesis Submitted  
in Partial Fulfilment of the Requirements  
for the Degree of  
Master of Technology**

by  
**P. NARAYANA RAO**

to the  
**DEPARTMENT OF INDUSTRIAL AND MANAGEMENT ENGINEERING  
INDIAN INSTITUTE OF TECHNOLOGY, KANPUR  
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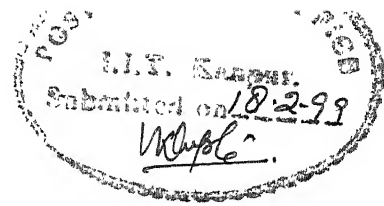
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## CERTIFICATE

This is to certify that the work contained in the thesis entitled "**MULTI-OBJECTIVE OPTIMISATION OF INJECTION MOLDING PROCESS PARAMETERS: A STUDY USING GENETIC ALGORITHMS**" by Mr. P. Narayana Rao has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

A handwritten signature in black ink, likely belonging to Professor T P Bagchi.

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Department of Industrial and Management Engineering  
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18 February, 1999

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# ABSTRACT

This study is an attempt to optimise process conditions in plastics injection molding by simulation guided by genetic algorithms. The object is to finally manufacture good quality molded products. In the present work, design of experiments, multiple regression and the meta-heuristic optimisation algorithm “genetic algorithm” are used to optimise the simulated process. Study is motivated by the fact that the quality of an injection molded part affected by many factors that are difficult to optimise on line. These include geometric parameters associated with the mold design and the cooling system design as well as the process parameters such as the molding conditions during the filling phase. In the present work we have focused on molding conditions only. Quality (captured as output or “response” from the simulation software) is quantified as a function of flow simulation outputs and constitutes the objective function that must be minimised. Second-order regression models are developed using the simulation outputs from two separate injection molding simulation softwares PARTADVISED (by MOLDFLOW) and 3D QUICKFILL (by CMOLD). The conflicting nature of the multiple objectives injection molding process parameters are discussed and handled by multi-objective GA. SGA and NSGA are used to solve the above problems.

# Chapter 1

## Introduction

This study is an attempt to synthesise several diverse engineering analysis and optimisation methods to help achieve the objective of superior product quality with multiple quality criteria. Injection molding of plastic parts is taken as the test process. Commercial simulators are used to provide process performance data for stated or specified process conditions. Multi-objective optimisation is attempted by meta-heuristic methods and a verification of the integrity of the overall methodology is attempted to conclude the study.

Chapter 2 presents an overview of multi-objective optimisation. Many real world problems involve multiple measures of performance, or objectives, which should be optimised simultaneously. In certain cases, objective functions may be optimised separately from each other and insight gained concerning the best that can be achieved in each performance dimension. However, multi-criteria solutions to the overall problem can seldom be found in this way. Optimal performance according to one objective, if such an optimum exists, often implies unacceptably low performance in one or more of the other objective dimensions, creating the need for a compromise to be reached (Fonesca and Fleming, 1995). A suitable solution to such problems involving conflicting objectives should offer “acceptable”, though possibly sub-optimal performance in the single-objective sense. Performance in *all* objective dimensions where “acceptable” is a problem-dependent is a subjective concept.

The conventional solution methods that are used in solving the multiobjective problems are mentioned in the chapter. What makes multiple criteria decision making (MCDM) complex is the plurality of the criteria involved in the problem. MCDM has seemed to emerged as the accepted nomenclature for all models and techniques dealing with multiple objective decision making. This chapter concludes with the citation of the *nondominated sorting genetic algorithm* (NSGA) (Deb and Srinivas, 1995), a meta-heuristic method used in the present work.

Chapter 3 describes the meta-heuristic multiobjective optimisation method based on genetic algorithms that is rapidly going popularity among engineers. Genetic algorithms were invented by John holland and were developed by Holland and his students and colleagues at the University of Michigan in the 1960s and the 1970s (Mitchell, 1996). This chapter provides an introduction to the genetic algorithms, discusses salient features of genetic algorithms and ends with the discussion of NSGA, the multi-objective genetic algorithm developed by Srinivas and Deb (1995), NSGA is used in the present work for solving a multiobjective engineering design problem.

Chapter 4 overviews injection molding. Injection molding process is a complex but highly efficient means of producing a large variety of thermoplastic products, particularly those with high volume production requirements, tight tolerances and complex shapes. The final product quality of injection molded part must include final material properties as well as structural and aesthetic considerations.

Injection molding is one of the most common and versatile operations for mass production of complex plastic parts with excellent dimensional tolerance. It requires minimal or no finishing or assembly operations. It is a cyclic process of forming plastic into a desired shape by forcing

the plastic material under pressure into a cavity. The shaping is achieved by cooling (for thermoplastics) or by a chemical reaction (for thermosets). Approximately 32% percent by weight of all plastics processed go through injection molding machines (C-MOLD Design guide, 1994). Historically, the major milestones in the development of injection molding are two: (1) the invention of the reciprocating-screw machine and (2) the application of computer simulation to the design and manufacture of plastic parts.

Product quality in injection molding is a function of the material used, the mold design and the processing conditions. The important processing conditions during the filling phase are the mold temperature, melt temperature and filling time. This chapter starts also overviews the different aspects of mold design are discussed, and the characteristics of the plastic material molded. Also discussed is how process parameters are characterised. The chapter concludes with an outline of how NSGA may be applicable to the optimisation of injection molding.

Chapter 5 describes the planning of injection molding *simulation* experiments, an effective way to evaluate and optimise injection molding operations *before* actual production begins in the factory. Plastics are an increasingly popular material for making parts in many industries including automotive, computer and consumer. The injection molding production process, a convenient way to make plastic parts, is nevertheless complex and extremely application-dependent. Previously, not all plastic parts could be analysed before production because of the time and expertise needed to undertake a simulation of the process before actual production began. This resulted in frequent and expensive part redesign and mold rework.

But the situation is changed, it has been now recognised that computer-aided engineering (CAE) incorporating process simulation enhances engineers ability to handle many all aspects of plastic injection molding, benefiting productivity, product quality, timeliness, and cost. The

process behaviour predicted by CAE can help novice engineers overcome the lack of previous experience and assist experienced engineers in pinpointing important or critical factors that may otherwise be overlooked.

Keeping in view the demands of the plastics industry, giants in the injection molding software business, namely MOLDFLOW and CMOLD, have developed two simulation software called PART ADVISER and 3DQUICKFILL respectively. Both these softwares now bring the benefits of process simulation directly to the desk of the product designer. In the present study both these softwares are used for generating the data required for the optimisation of molding parameters.

The techniques of multiple regression are reviewed in Chapter 6. In any system in which variable (input) quantities change, the interest might be in assessing the effects of the factors on the behaviour of some measurable quantity (the response). Such an assessment is possible through regression analysis. Regression analysis is a statistical technique for investigating and modelling the relationship between variables. Using data collected from a set of experimental trials, regression helps to establish empirically (by fitting some form of mathematical model) the type of relationship that is present between the response variable and its influencing factors. The ‘output’ variable is the dependent variable here and is called the *response*. The influencing factors are called *predictor*, *regressor*, or *input* variables. Chapter 6 also summarises a number of experimental plans to sample the response region. These different plans aim at producing good “predictor” models while keeping the experimental effort as economical as possible.

Chapter 7 summarises the results of the different multi-criteria optimisation attempted in this study. Results obtained from executing the simple genetic algorithm (SGA) and NSGA are

presented in this chapter. The convergence graphs from the results of SGA and the Pareto diagrams resulting from multicriteria optimisation by NSGA are shown.

Chapter 8 comprises the conclusions and scope for the future work.

## Chapter 2

# MULTIOBJECTIVE OPTIMISATION

Many real world problems involve multiple measures of performance, or objectives, which should be optimised simultaneously. In certain cases, objective functions may be optimised separately from each other and insight gained concerning the best that can be achieved in each performance dimension. However, suitable solutions to the overall problem can seldom be found in this way. Optimal performance according to one objective, if such an optimum exists, often implies unacceptably low performance in one or more of the other objective dimensions, creating the need for a compromise to be reached (Fonesca and Fleming, 1995). A suitable solution to such problems involving conflicting objectives should offer “acceptable”, though possibly sub-optimal in the single-objective sense, performance in all objective dimensions, where “acceptable” is a problem-dependent and ultimately subjective concept. In this chapter the concept of “ multiobjective optimisation” is discussed. The conventional solution methods that are used in solving the multiobjective problems are mentioned. This chapter concludes with the citation of the *nondominated sorting genetic algorithm* (NSGA) (Deb and Srinivas, 1995), which is used in the present work.

## 2.1 Multiple Criteria Decision Making

### 2.1.1 Definition of Multiple criteria Decision Making

*The process of decision making is the selection of an act or courses of action from among alternatives acts or courses of actions such that it will produce optimal results under some criteria of optimisation* (Tabucanon, 1989). This concise definition of decision making invokes further elaboration to a certain extent. Before the problems can be considered well-defined, the set of alternatives and the set of criteria have to be known and established first; only then can the selection process commence. What makes multiple criteria decision making complex is the plurality of the criteria involved in the problem. In decision analysis of complex systems, such terms as “multiple criteria”, “multiple objectives”, or “multiple attributes” are used to describe decision situations. Often these terms are used interchangeably. Certainly there are no universal definitions of these terms. Multiple criteria decision making (MCDM) has seemed to emerged as the accepted nomenclature for all models and techniques dealing with multiple objective decision making or multiple attribute decision making.

### 2.1.2 Examples

Some examples of the Multiple Criteria Decision Making

#### *Production Planning*

Max { Total net revenue }

Max { Minimum net revenue in any period }

Min { Backorders }

Min { Overtime }

Min { Finished goods inventory }

## *Capital Budgeting*

Max { Net present value }

Min { Capital investment requirements }

Min { Annual operating expenses }

Max { Investment in projects related to environmental protection }

Max { Investment in projects in a given geographical area }

Max { Investment in projects pertaining to a given product line }

Multiplicity of criteria occurs in almost every area of business decision making and operations. Examples are numerous and more straightforward than those listed so far. They appear in accounting, finance, operations management, marketing, manpower planning, personnel selection, etc.,

The general multiobjective problem requiring the optimisation of  $k$  objectives simultaneously may be formulated as follows.

$$\text{Max (min)} \quad Z_j = f_j(X), j=1,2,\dots,k$$

Subject to

$$g_i(X) \leq b_i, \quad i=1,2,\dots,m$$

$$X \geq 0$$

where  $X$  is a vector of decision variables and  $g_i(X)$  are the inequality constraints. In multicriterion optimisation, because the objectives are conflicting, there does not exist a single unique solution which is the globally maximum or globally minimum with respect to all the conflicting objectives. The increase in any of these objectives will decrease the others and vice versa.

## 2.2 Conflicting Criteria

A necessary condition of MCDM is the presence of more than one criterion. The sufficient condition is that the criteria must be *conflicting* in nature. In summary, a problem can be considered as that of MCDM if and only if there appears at least two *conflicting* criteria and there are at least two *alternatives* solutions (Tabucanon, 1989).

Criteria are said to be in conflict if the full satisfaction of one will result in impairing or precluding the full satisfaction of the other(s). The criteria are considered to be “strictly” conflicting if the increase in satisfaction of one results in a decrease in satisfaction of the other. The sufficient condition of MCDM, however, does not necessarily stipulate “strictly” conflicting criteria.

In view of the conflicting nature of the criteria involved in MCDM, choosing the “best” alternatives is indeed a difficult task for the decision maker. Consequently there is a need for methods to systematically resolve the conflicts among criteria (or objectives) in order to reach acceptable compromises and come up with satisfying (or termed as “satisficing”) solutions.

## 2.3 Classification of Multiobjective Problems

There are several ways to classify the different approaches to multiobjective optimisation.

Adulbhan and Tabucanon (1980) classified the techniques into three main approaches based on the way the initial multiobjective problem is transformed into a mathematically manageable format. These approaches are respectively,

- (a) Conversion of secondary objectives into constraints,
- (b) Development of a single combined objective function, and
- (c) Treatment of all objectives as constraints.

Hwang, Masud, Paidy and Yoon (1982), on the other hand, proposed a different classification. They based their grouping of techniques according to the stage at which information from the decision maker is needed by the analyst. The classification is divided into four approaches ,

- (a) No articulation of preference information,
- (b) “a priori” articulation of preference information,
- (c) Progressive articulation of preference information, and
- (d) “a posterior” articulation of preference information.

Among others, who have published survey papers on multiobjective optimisation, are Johnson (1968), Roy (1971), Cochrane and Zeleny (1973), Lietmann and Marzollo (1975) and Hwang and Masud (1975).

## 2.4 Solution Methods

### 2.4.1 Single Objective Approach (Tabucanon, 1989)

This is the simplest way of handling the multiobjective optimisation problems. If you consider a multiobjective problem with  $k$  objectives, optimise one objective (the most *important* one) and to treat the resulting  $k-1$  objectives as “secondary” objectives into constraints. This is done by specifying a maximum (for minimisation) or minimum (for maximisation) level of attainment for each of the secondary objectives. Thus, the multiobjective problem is converted into the single objective optimisation problem, as follows,

$$\text{Maximise } Z_1 = f_1(X)$$

Subject to

$$g_i(X) \leq b_i, \quad i = 1, 2, \dots, m \text{ (original constraints)}$$

$$f_j(X) \geq z_j^1, \quad j = 2, 3, \dots, k \text{ (additional constraints)}$$

$$X \geq 0$$

where  $z_j^1$  are specified minimum levels of attainment allowed of the remaining objectives. In this formulation it is assumed that all the objectives are of maximising nature. Although this method is practical, there are certain cases where the approaches gives no defined feasible region after the introduction of the additional (k-1) constraints.

## 2.4.2 Utility Function Method (Tabucanon, 1989)

This utility function method converts the multiobjective optimisation problem into a single objective problem in the following form:

$$\text{Maximise} \quad Z = F[f_1(X), f_2(X), \dots, f_k(X)]$$

Subject to

$$g_i(X) \leq 0, \quad i = 1, 2, \dots, m$$

$$X \geq 0$$

Where F is the utility function of the multiple objectives, representing the decision maker's preferences. If F is properly determined, the solutions obtained will ensure the decision maker's satisfaction. However, the determination of F will be a extremely difficult sometimes. Depending on the problem F takes many forms, the most common form assumes that the decision maker's utility function is additively separable with respect to the objectives. Thus the additive utility function method converts the objectives functions into one of the following form:

$$\text{Maximise} \quad Z = \sum_{j=1}^k F_j[f_j(X)]$$

$F_j$  is used in the same manner as attaching a weight to each objective function. Thus, the problem is transformed into the following:

$$\text{Maximise} \quad Z = \sum_{j=1}^k w_j f_j(X)$$

Where  $w_j$  indicates the relative importance of objective  $j$ , and this is determined “a priori”.

### 2.4.3 Global Criterion Method (Rao, 1994)

In this method the optimum solution  $X^*$  is found by minimising a preselected global criterion,  $F(X)$ , such as the sum of the squares of the relative deviations of the individual objective functions from the feasible ideal solutions. Thus  $X^*$  is found by minimising

$$F(X) = \sum_{i=1}^k \left\{ \frac{f_i(X_i^*) - f_i(X)}{f_i(X_i^*)} \right\}^p$$

Subject to

$$g_j(X) \leq 0, \quad j=1, 2, \dots, m$$

$$X \geq 0$$

where  $p$  is a constant and  $X_i^*$  is the ideal solution for the  $i$ th objective function. The solution  $X_i$  is obtained by minimising  $f_i(X)$  subject to the constraints  $g_j(X) \leq 0, j=1, 2, \dots, m$ .

### 2.4.4 Bounded Objective Function Method (Rao, 1994)

In this method, the minimum and the maximum acceptable achievement levels for each objective function  $f_i$  are specified as  $L^{(i)}$  and  $U^{(i)}$ , respectively, for  $i = 1, 2, \dots, k$ . Then the optimum solution  $X^*$  is found by minimising the most important objective function, say, the  $k$ th one as follows:

$$\text{Minimise} \quad f_r(X)$$

Subject to

$$g_j(X) \leq 0, \quad j=1, 2, \dots, m$$

$$L^{(i)} \leq f_i \leq U^{(i)}, \quad i = 1, 2, \dots, k, i \neq r$$

### 2.4.5 Lexicographic Method (Rao, 1994)

In this method, the objectives are ranked in order of their importance to the decision maker. The optimum solution  $X^*$  is found by minimising the objective function starting with the most important one and proceeding according to the order of importance of the objectives. The subscripts of the objectives indicate not only the objective function number, but also the priorities of the objectives. Thus  $f_1(X)$  and  $f_k(X)$  denote the most and least important objective functions, respectively. The first problem is formulated as

Minimise  $f_1(X)$

Subject to

$$g_j(X) \leq 0, j = 1, 2, \dots, m$$

and its solution  $X_1^*$  and  $f_1^* = f_1(X_1^*)$  is obtained. Then the second problem is formulated as

Minimise  $f_2(X)$

Subject to

$$g_j(X) \leq 0, j = 1, 2, \dots, m$$

and

$$f_1(X) = f_1^*$$

Solution of this problem is obtained as  $X_2^*$  and  $f_2^* = f_2(X_2^*)$ . This procedure is repeated until all the  $k$  objectives have been considered. The  $i$ th problem is given by

Minimise  $f_i(X)$

Subject to

$$g_j(X) \leq 0, j = 1, 2, \dots, m$$

and

$$f_l(X) = f_l^*, l = 1, 2, \dots, i-1$$

and its solution is found as  $X_i^*$  and  $f_i^* = f_i(X_i^*)$ . Finally the solution obtained at the end (i.e.,  $X_k^*$ ) is taken as the desired solution  $X^*$  of the original multiobjective optimisation problem.

#### 2.4.6 Goal Programming Method (Rao, 1994)

In the simplest version of goal programming, the analyst sets goals for each objective that he wishes to attain. The optimum solution  $X^*$  is then defined as the one which minimises the deviations from the set goals. Thus the goal programming formulation of the multiobjective optimisation problem leads to

$$\text{Minimise } Z = \sum_{j=1}^k \left[ (d_j^+ + d_j^-)^p \right]^{1/p}, p \geq 1$$

Subject to

$$g_j(X) \leq 0, \quad j = 1, 2, \dots, m$$

$$f_j(X) + d_j^+ - d_j^- = b_j, \quad j = 1, 2, \dots, k$$

$$d_j^+ \geq 0, \quad j = 1, 2, \dots, k$$

$$d_j^- \geq 0, \quad j = 1, 2, \dots, k$$

$$d_j^+ d_j^- = 0, \quad j = 1, 2, \dots, k$$

where  $b_j$  is the goal set by the designer for the  $j$ th objective and  $d_j^+$  and  $d_j^-$  are, respectively, the under-achievement and over-achievement of the  $j$ th goal. The value of  $p$  is based upon the utility function chosen by the designer. Often the goal for the  $j$ th objective,  $b_j$ , is found by first solving the problem,

$$\text{Minimise } f_j(X)$$

Subject to

$$g_j(X) \leq 0, \quad j = 1, 2, \dots, m$$

All the conventional methods discussed above essentially convert a multiple objective optimisation problem into a single objective problem by some means or the other. No method takes care of optimising all the objectives simultaneously to obtain a set of solutions (such as the “Pareto optimal” or “efficient” solutions) which offer a way to simultaneously “satisfice” all objectives (Simon, 1969). Some specially constructed evolutionary algorithms (EA’s), however, have been recognised to be possibly well-suited to multiobjective optimisation since early in their development. Multiple individuals can search for multiple solutions in parallel, eventually taking advantage of any similarities available in the family of possible solutions to the problem. The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of EA’s in multiobjective search and optimisation, which is perhaps a problem area where Evolutionary Computation really distinguishes itself from its competitors (Carlos, 1995). Pareto-based ranking fitness assignment was first proposed by Goldberg (1989), as a means of assigning equal probability of reproduction to all non-dominated individuals in the population. The method consists of assigning rank 1 to the non-dominated individuals and removing them from contention, then finding a new set of non-dominated individuals, ranked 2, and so forth. Srinivas and Deb (1995) have implemented Goldberg’s nondominated sorting in GA’s along with a niche and speciation method to find multiple Pareto-optimal points simultaneously, called Nondominated Sorting Genetic Algorithm (NSGA). This algorithm is used in the present work for solving our multiobjective problem, Optimisation of Injection molding process parameter.

## **2.5 The Concept of Pareto Optimality**

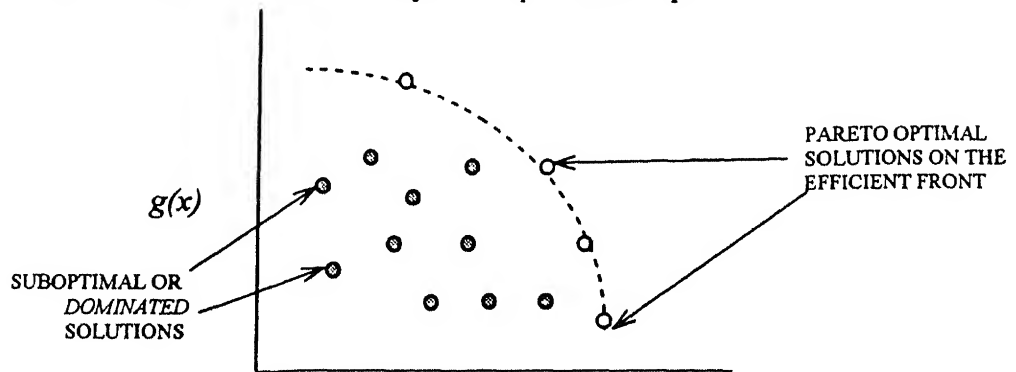
The family of solutions of a multiobjective optimisation problem with conflicting objectives is composed of all those elements of the search space which are such that the components of the

corresponding objectives vectors cannot be all simultaneously improved. This is known as the concept of Pareto optimality.

A more formal definition of Pareto optimality is as follows. Consider, without loss of generality, the minimisation of the  $n$  components  $f_k$ ,  $k=1, \dots, n$ , of a vector function  $f$  of a vector variable  $x$  in a universe  $U$  is said to be Pareto-optimal if and only if there is no  $x_v \in U$  for which  $\mathbf{v} = f(x_v) = (v_1, \dots, v_n)$  dominates  $\mathbf{u} = f(x_u) = (u_1, \dots, u_n)$ , i.e., there is no  $x_v \in U$  such that

$$\forall i \in \{1, \dots, n\}, v_i \leq u_i \quad \cap \quad \exists i \in \{1, \dots, n\} \mid v_i < u_i$$

The set of all Pareto-optimal decision vectors is called the *Pareto-optimal, efficient, or admissible set* of the solutions. The corresponding set of objective vectors is called the *non-dominated set*. In practice, however, it is not unusual for these terms to be used interchangeably to describe solutions of a multiobjective optimisation problem.



**Figure 1.1.** The Efficient Front in a Bi-objective Maximisation Problem

The notion of Pareto-optimality is only a first step towards the practical solution of a multiobjective problem. This decision involves selecting subsequently a single compromise

solution from the non-dominated set according to some preference information. All other solutions are dominated in the pareto sense and they may be ignored.

## Chapter 3

### GENETIC ALGORITHMS

Genetic algorithms were invented by John Holland in the 1960s and were developed by Holland and his students and colleagues at the University of Michigan in the 1960s and the 1970s (Mitchell, 1996). This chapter starts with the introduction to the genetic algorithms, discusses salient features of genetic algorithms and ends with the discussion of NSGA, a multiobjective genetic algorithm developed by Srinivas and Deb (1995). NSGA is used in the present work for solving a multiobjective engineering design problem.

#### 3.1 What are Genetic Algorithms (GAs) ?

**Evolution in a changing world :** Looking at the world around us, we see a staggering diversity of life. Millions of species, each with its own unique behaviour patterns and characteristics, abound. Yet, all of these plants and creatures have evolved, and continue evolving, over millions of years. They have adapted themselves to a constantly shifting and changing environment in order to survive. These weaker members of a species tend to die away, leaving the stronger and fitter to mate, create offspring and ensure the continuing survival of the species. Their lives are dictated by the laws of natural selection and Darwinian evolution. And it is upon these ideas that genetic algorithms are based.

What exactly do we mean by the term GA? Goldberg (1975) defines it as follows:

*Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics.*

GAs exploit Charles Darwin's idea of the survival of the fittest and an interbreeding population to create a novel and innovative global search strategy. A population of coded strings of alphabets or numbers representing solutions to a specified problem, is maintained by the GA. The GA then iteratively creates new populations from the old by ranking the strings according to their fitness and interbreeding the fittest to create new strings, which are (hopefully) closer to the optimum solution to the problem at hand. So in each generation, the GA creates a set of strings from the bits and pieces of the previous strings as it occurs in the mating of organisms in nature occasionally adding random new data to keep the population from stagnating. The end result is a search strategy that is tailored to probe vast, complex, multimodal search spaces.

GAs are a form of randomised search, in that the way in which strings are chosen and combined is a stochastic process. This is a radically different approach to the problem solving methods used by more traditional algorithms, which often use gradient information and tend to be more deterministic in nature.

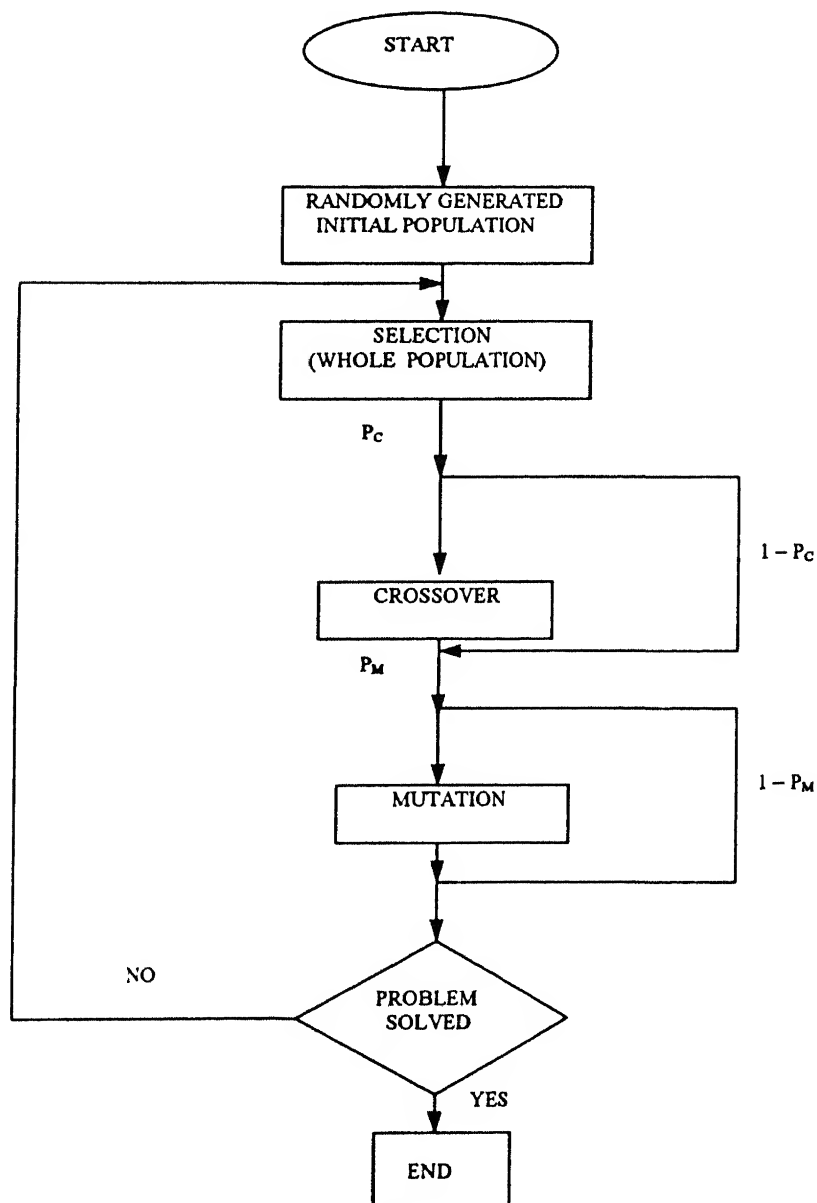
The idea of survival of the fittest is of great importance to genetic algorithms. GAs use what is termed as a fitness function in order to select the fittest string that will be used to create new, and conceivably better, populations of strings. The fitness function takes a string and assigns a relative fitness value to the string. The method by which it does this and the nature of the fitness value does not matter. The only thing that the fitness function must do is to rank the strings in some way by producing the fitness value. These values are then used to select the fittest strings (Holland, 1992).

### **3.2 Genetic Algorithms: A Natural Perspective**

The population can be simply viewed as a collection of interacting creatures. As each generation of creatures comes and goes, the weaker ones tend to die away without producing

children, while the stronger mate, combining attributes of both parents, to produce new, and perhaps unique children to continue the cycle. Occasionally, a mutation creeps into one of the creatures, diversifying the population even more. Remember that in nature, a diverse population within a species tends to allow the species to adapt to its environment with more ease. The same holds true for genetic algorithms.

**Figure 3.1:** The iteration loop of a Simple Genetic Algorithm



The flowchart above shows the iterative cycle of a basic genetic algorithm. Firstly, an initial population of strings is created. The process then iteratively selects individuals from the population that undergo some form of transformation (via the recombination step) to create a new population. The new population is then tested to see if it fulfils some stopping criteria. If it does, then the process halts, otherwise another iteration is performed.

### **3.3 GAs and Robustness**

Two remarkable traits of biological systems in general are their robustness and flexibility. Biological systems have methods for self-guidance, self-repair and reproduction. Very few artificial systems have any of these features.

GAs demonstrate at least some of these desirable traits from nature. At least intuitively, we may think so because genetic algorithms are modelled closely on evolution occurring in the biological world. Genetic algorithms have proven to be robust, flexible and efficient in optimising vast and complex solution spaces.

### **3.4 Genetic Algorithm Traits**

Genetic algorithms provide robustness, efficiency and flexibility when searching a problem space for the optimum solution. But why is this? For a more technical look at the power of GAs, a discussion on building blocks and schemata is required. For the moment, we shall just cast a very brief look at the GA search strategy.

GAs judiciously use the idea of randomness when performing a search. However, it must be understood that GAs are not simply random search algorithms. Random search algorithms are inherently inefficient due to the directionless nature of their search. GAs are *not* directionless. They utilise knowledge from previous generations of strings in order to construct a new

generation that will approach the optimal solution. In other words, GAs use past knowledge to direct the search. Such search algorithms are known as intelligent randomised search techniques.

### **3.5 Difference between Genetic Algorithms and Traditional Methods**

The following are the essential differences between GAs and other forms of optimisation (Goldberg, 1989)

1. Genetic algorithms use a coded form of the function values (parameter set), rather than with the actual values themselves. For example, if we want to find the minimum of the function  $f(x) = x^3 + x^2 + 5$ , the GA would not deal directly with  $x$  or  $y$  values, but with strings that encode these values. For this case, strings representing binary  $x$  values should be used.
2. Genetic algorithms use a set, or population, of points to conduct a search, not just a single point on the problem space. This gives GA the power of searching noisy spaces littered with local optimum points. Instead of relying on a single point to search through the space, the GA looks at many different areas of the problem space at once, and uses of this information to guide it.
3. Genetic algorithms use only payoff information to guide themselves through the problem space. Many search techniques need a variety of information to guide themselves. Hill climbing methods require the derivative, for example. The only information a GA needs is some measure of fitness about a point in the space (sometimes known as an objective function value). Once the GA knows the current measure of “goodness” about a point, it can use this to continue searching for the optimum.

- 4 GAs are probabilistic in nature not deterministic This is a direct result of the randomisation techniques used by GAs
- 5 GAs are inherently parallel Here lies one of the most powerful features of genetic algorithms GAs, by their nature, are very parallel, dealing with a large number of points (strings) simultaneously. Holland has estimated that a GA processing  $n$  strings at each generation, the GA in reality processes  $n^3$  useful substrings This becomes cleared when schemata are examined

### **3.6 Basic Genetic algorithm operations**

The following three basic operations are found in almost every genetic algorithm implementation

- 1 Reproduction
- 2 Crossover
- 3 Mutation

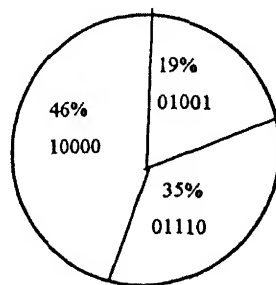
#### **3.6.1 Reproduction**

Reproduction is usually the first operator applied on a population (Deb, 1995) Reproduction selects good strings in a population and forms a mating pool That is why the reproduction operator is sometimes known as the selection operator. The reproduction operator allows individual strings to be copied for possible inclusion in the next generation The chance that a string will be copied is based on the string's fitness value, calculated from a fitness function For each generation, the reproduction operator chooses strings that are placed into a mating pool, which is used as the basis for creating the next generation. For example, look at the table below

Strings	Fitness Value	Percentage
01001	5	19%
1000	12	46%
01110	9	35%

From the table, it is obvious that the string 10000 is the fittest, and should be selected for reproduction approximately 46% of the time. 01001 is the weakest, and should only be selected 19% of the time. One always selects the fittest and discards the worst, statistically selecting the rest of the mating pool from the remainder of the population.

For the moment we shall look at the most commonly used reproduction method in GAs. The Roulette wheel method simply chooses the strings in a statistical fashion based solely upon their relative (i.e., percentage) fitness values. To look abstractly at this method, consider the roulette wheel below, which is based on the previous example above.



**Figure 3.2: Roulette wheel selection**

When selecting the three strings that will be placed in the mating pool, the roulette wheel is spun three times, with the results indicating the string to be placed in the pool. It is obvious from the above wheel that there's good chance that string 10000 will be selected more than once. Multiple copies of the same string can exist in the mating pool. This is even desirable,

since the stronger strings will begin to dominate, eradicating the weaker (less fit) ones from the population. However, there are difficulties with this, as it can lead to premature convergence on a local optimum.

There exist a number of reproduction operators in GA literature, but the essential idea in all of them is that the above-average strings are picked from the current population and their multiple copies are inserted in the mating pool in a probabilistic manner. The following are five commonly used schemes:

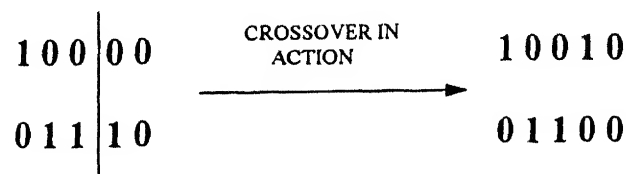
1. **Proportional (Roulette Wheel) Selection** This is discussed in the reproduction section in detail. This method will only work with fitness values from zero (non-negative) and scaling may sometimes be necessary. It has been shown that proportional selection performs poorly compared with other selection schemes in many GA problems.
2. **Tournament Selection** Choose  $t$  individuals at random from the population and copy the best individual from this group into the new population. Repeat  $N$  times.
3. **Truncation Selection** . With truncation selection that has a threshold of  $T$  between 0 and 1, only the fraction  $T$  best individuals can be selected. They all have the same selection probability.
4. **Linear Ranking Selection** The individuals are sorted according to their fitness values and the rank  $N$  is assigned to the best individual, the rank 1 assigned to the worst. The selection probability is linearly assigned to the individuals according to their rank and a selection equation.

**Exponential Ranking Selection** This follows the same methodology of linear ranking selection, the only difference being that the probabilities of the rank individuals are exponentially weighted.

### 3.6.2 Crossover

Once the mating pool is created, the next operator in the GA's arsenal comes into play. Crossover in biological terms refers to the blending of chromosomes from the parents to produce new chromosomes for the offspring. The analogy carries over to crossover in GAs.

The mating pool represents the population of parent strings that survive to create child strings that survive to create child strings (Ritzel, Eheart and Ranjithan, 1994). Children are created in a process known as crossover. Crossover begins by selecting two strings at random from the mating pool. Next, a crossover site is randomly selected for the two strings. The site can be between any two genes in the string. The genetic material after the crossover site is then exchanged between the two selected strings. These two new strings are considered "children" and form the members of a new population. The genetic operation of crossover is performed on each mated pair with a certain probability, referred to as crossover probability ( $P_c$ ). The crossover probability is typically set so that crossover probability parameter is typically set so that crossover is performed on most, but not all of the population. The end result in the creation of a new population which is the same size as the old population, and which consists mostly of children strings whose parents no longer exist and a minority of parents lucky enough to enter the new population unaltered.

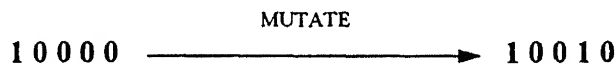


**Figure 3.3: One point crossover**

### 3.6.3 Mutation

Selection and crossover alone can obviously generate a staggering amount of differing strings. However, depending on the initial population chosen, there may not be enough variety of strings to ensure the GA sees the entire problem space, or the GA may find itself converging on strings that are not quite close to the optimum it seeds due to a bad initial population

Some of these problems are overcome by introducing a mutation operator into the GA. The GA has a mutation probability,  $P_m$ , which dictates the frequency at which mutation occurs. For each string element in each string in the mating pool, the GA checks to see if it should perform a mutation. If it should, it randomly changes the element value to a new one. In binary strings, 1s are changed to 0s and 0s to 1s. For example, the GA decides to mutate bit position 4 in the string 10000



**Figure 3.4: Mutation**

The resulting string is 10010 as the fourth bit in the string is flipped

Mutation will help in preventing the population from stagnating, mutation helps to maintain that diversity throughout the GA's iterations.

One of the major issues in GAs is the relative importance of two genetic operators: mutation and crossover (William, 1993). In the 1960's, L. Fogel et al. (1966) illustrated how mutation and selection can be used to evolve finite state automata for a variety of tasks. Rechenberg (1973) investigated "evolution strategies" that again concentrate on mutation as the key genetic operator. D. Fogel has continued the earlier work of L. Fogel and makes an even stronger claim that crossover has no general advantage over mutation (Fogel & Atmar, 1990). On the other hand, proponents of the Holland (1975) style of genetic algorithms believe that

crossover is the more powerful of the two operators. Considerable effort has been spent in analysing crossover and its effects on performance (e.g., Dejong 1975, Spears & Dejong, 1991). In most of these analyses mutation is considered to be a background operator and of secondary importance. To support these views, experimental results have been presented, illustrating the power of crossover (e.g., Dejong, 1975) Schaffer & Eshelman (1991) compared mutation and crossover, and conclude that mutation alone is always sufficient. Upto date there has been no theoretical justification to support either group's beliefs. It has never been theoretically shown that crossover is any sense more powerful than mutation, or that mutation is more powerful than crossover. Similarly, no theoretical basis exists for supposing that both operators are necessary and perform different roles within the GA (William, 1993).

### 3.7 Schemata : The Building Blocks of GAs

The basic idea behind building blocks is that very fit individuals in a population pass on high performance notions to their children. These notions take the form of substrings. It stands to reason that strings with a high fitness value must contain a substring that is a primary cause of such a high fitness. Thus, even though crossover may splice the string into two, there may be good chance that the highly fit substring is passed on to the children. These highly fit substrings are known as *building blocks*.

Schemata are templates of strings that describe similarity between certain sets of strings. In order to define a schema, the following alphabet is used

Binary Alphabet	Meaning
0	Binary 0 in string
1	Binary 1 in string
*	Bits value is unspecified

The alphabet {0, 1, \*} can be used to represent any pattern of binary substrings. For example

Schema Matching strings	
* 1 1 1 1	0 1 1 1 1 1 1 1 1 1
* 0 1 0 * 0	1 0 1 0 1 0 0 0 1 0 1 0  1 0 1 0 0 0 0 0 1 0 0 0
* * 1 * 0	0 0 1 0 0

Now we look at how our basic GA operators affect the processing of schemata. In reproduction, the effect is obvious. Fitter strings get selected for the mating pool more than weaker strings, and thus fitter schemata have a greater chance of being involved in the creation of the next generation than their weaker counterparts. Crossover has a huge impact on the GA building blocks. Obviously, every time crossover occurs, there is a chance that useful schemata might be destroyed by the splicing process. This is one of the main reasons why crossover should not be performed 100% of the time. Looking at the following two schemata, we can define the *length* of a schema to be the distance between the first and last specific string position.

Schemata Length	
* * 0 * * *	0
1 * * 1 * *	3
* 0 * 1 * 1	4

From the above table, it is intuitively to see that useful shemata of long length are far more easily disrupted than schemata of short length

The *order* of a schema to be the number of fixed positions in the schema.

Schema order	
* 0 * * *	1
1 0 * 0 * *	3
1 1 1 * * 0	4

The higher the order of a schema, the more specific the schema becomes obviously, “1 0 0 \* 1” is far more specific than “\* \* 0 \* \*”. Again, with crossover, it is obvious that schemata with small orders have a less likely chance of being disrupted than schemata with high orders. A high mutation rate will badly disrupt schemata, which is why a very low mutation rate is always advised for most GAs.

A couple of conclusions from building blocks theory are of importance to note. *Strings with higher fitness schemata of short length will have a high likelihood of being selected to create the next population., and thus pass on those schemata to strings integrated the new population.* It has been shown that schemata of this form increase in number from one population to the next in an exponential fashion. In other words,  $n^3$  useful schemata are processed per generation, and the majority of these have small orders and lengths associated with them. These schemata are what gives a GA the power to efficiently search through a problem space. This  $n^3$  feature is so important to GA s that it has been given a special name, *implicit parallelism*.

The genetic algorithms implicit parallelism allows it to test and exploit large numbers of regions in the search space while manipulating relatively few strings. Implicit parallelism also helps genetic algorithms to cope with nonlinear problems, those in which the fitness of string

containing two particular building blocks may be much greater (or much smaller) than the sum of the fitness attributable to each building block alone (Holland, 1992)

### **3.8 Uses of GAs in the Real world**

Although the previous pages dealt that with GAs solely as a optimisation technique, there are a huge diversity of fields using GA technology for all sorts of different applications Below are just a small sampling of the staggering number of applications that put GAs to use

- 1 Criminal Suspect Recognition
- 2 Music composition
- 3 Construction and Training of Neural Networks
- 4 Scheduling problems
- 5 Games playing
- 6 Prisoner's Dilemma
- 7 Earthquake Epicenter Detection
- 8 Structural Optimisation
- 9 Function Optimisation
- 10 Database Query Optimisation
- 11 Aircraft Design
- 12 Determination of Protein Structures

### **3.9 THE NONDOMINATED SORTING GENETIC ALGORITHM : NSGA**

#### **3.9.1 Introduction**

Many real-world design or decision-making problems involve simultaneous optimisation of multiple objectives In principle, multiobjective optimisation is very different from single-

objective optimisation (Srinivas, 1998) In single-objective optimisation, one attempts to obtain the *best* design or decision, which is usually the global minimum or the global maximum, depending on whether the optimisation problem is one of minimisation or maximisation In the case of multiple objectives, there may not exist one solution that is best (global minimum or maximum) with respect to all objectives In a typical multiobjective optimisation problem, there exists a set of solutions that are superior to the rest of solutions in the search space when all objectives are considered but are inferior to other solutions in the space in one or more objectives These solution are known as *Pareto-optimal* solutions or *nondominated* solutions

Conventional optimisation techniques are difficult to extend to the *true* multiobjective case, because they were not designed with multiple solutions in mind Evolutionary algorithms, has been recognised to be possibly well-suited to multiobjective optimisation since early in their development Multiple individuals can search for multiple solutions in parallel, eventually taking advantage of any similarities available in the family of possible solutions to the problem The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of Evolutionary algorithms in multiobjective search and optimisation, which is perhaps a problem area where Evolutionary Computations really distinguishes itself from its competitors (Fonseca and Fleming, 1995)

### **3.9.2 Genetic Algorithm and Multiple Objective Optimisation**

The simplest genetic algorithm is sufficient for solving a single objective problem, with a single solution Multiple objective optimisation, however, entails finding a set of solutions along the trade-off surface between the objectives In order to accommodate a problem with

two or more objectives, extensions to the simple genetic algorithm have been developed (Ritzel, Eheart and Ranjithan, 1994)

The conceptually simplest way to use genetic algorithm to solve a multiple objective optimisation problem is to code the GA in such a manner that all the objectives, except for one, are constant (constrained to single value) The remaining objective becomes the fitness function for the GA Through the process of running the GA numerous times with different values of the constrained objectives, a trade-off surface can be developed This process can be tedious and time consuming In addition coding objectives as constants may be difficult or impossible for certain problems

Schaffer (1984) developed a population based non-Pareto method, called Vector Evaluated Genetic Algorithm (VEGA) In this method appropriate fractions of the next generation, or sub-population, were selected from the whole of the old generation according to each of the objectives, separately Crossover and mutation were applied as usual after shuffling all the sub-populations together Although Schaffer (1984) was able to identify various solutions along the trade-off surface of his test functions during a VEGA a run, the algorithm always ultimately converged to a single solution (Ritzel, Eheart and Ranjithan, 1994) Richardson et al. (1989) reported that the effect of the VEGA is the same as that of using a linear combination of objectives in a single fitness function

Fourman, kursaw, and Hajela and Lin, all attempted to promoted the generation of multiple non-dominated solutions, a goal at which they reported achieved a reasonable degree of success (Fonseca and Fleming, 1995) However, none makes *direct* use of the actual definition or Pareto-optimality

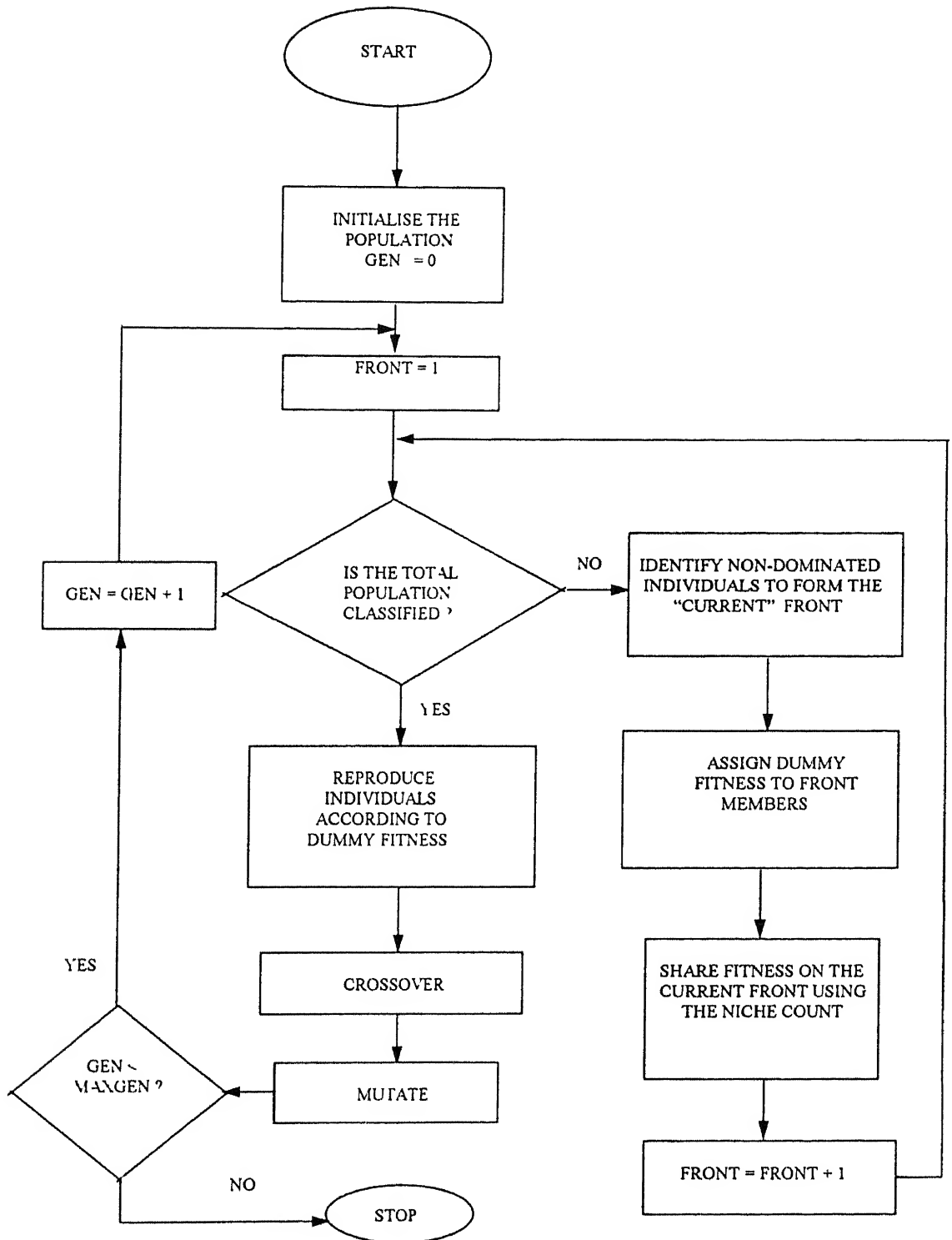
Pareto-based fitness assignment was first proposed by Goldberg(1989), as a means of assigning equal probability of reproduction to all non-dominated individuals in the population. This method involves finding the set of strings in the population that are Pareto nondominated by the rest of the population. These strings are then assigned the highest rank and eliminated from further contention. Another set of Pareto nondominated strings are determined from the remaining population and are assigned the next highest rank. This process continues until the population is suitably ranked.

Fonseca and Fleming (1995) have proposed a slightly different scheme, whereby an individual's rank corresponds to the number individuals in the current population by which it is dominated. Non-dominated individuals are, therefore, all assigned the same rank, while dominated ones are penalised according to the population density in the corresponding region of the trade-off surface. The algorithm proceeds by sorting the population according to the multiobjective ranks previously determined. Fitness is assigned by interpolating, e.g., linearly, from the best to the worst individuals in the population, and then averaging it between individuals with the same multiobjective rank. This multiobjective optimisation algorithm uses a niche-formation method to distribute the population over the Pareto-optimal region. But instead of performing sharing on the genotype and phenotype parameter values, sharing is done on objective function values. Hence even though this maintains diversity in the objective function values, this may not maintain diversity in the parameter set, a matter of importance for a decision maker. Moreover, this algorithm would not find multiple solutions in problems with different Pareto-optimal points correspond to the same objective function value (Jayaram, 1998).

### 3.9.3 Nondominated Sorting Genetic Algorithm (NSGA)

NSGA is based on the Goldberg's suggestion (1989). The idea behind the nondominated sorting GA procedure is that a *ranking selection* method is used to emphasise good solutions and a niche method is used to maintain a stable subpopulation of good solutions. NSGA differs from simple genetic algorithm only in the manner the *selection* operator works. In NSGA Crossover and Mutation operators work same as in the simple genetic algorithm. However, before selection is performed, the population is *ranked* on the basis of the nondominated sorting concept, to emphasise Pareto-optimality. Figure 3.5 (Deb and Srinivas, 1995) shows the flow chart of NSGA algorithm.

NSGA starts with the generation of initial set of solutions as any GA. From the initial population, the nondominated solutions are first identified. These "nondominated" individuals are considered to constitute the first nondominated front in the initial population and assigned a *dummy fitness value*, equal to population size (Srinivas, 1998). The dummy fitness value is assigned to the initial set of population is to give equal reproductive chance to all these nondominated solutions in the front. To maintain diversity in the population, "sharing" (which is explained in the following section) is done on the classified individuals. Next, the nondominated individuals are ignored to process the rest of the population in the same way to identify individuals for the second nondominated front. Then dummy fitness value less than that of the previous front is assigned to the second front. This is done to differentiate between the members of the first front and the members of the second front. Then, sharing is done on the second front, and this process is continued until the whole population is evaluated, and classified into successive fronts. This process leads to the creation of several successive fronts.



**Figure 3.5** Flowchart of NSGA  
(Deb and Srinivas, 1995)

of “nondominated” individuals. After the whole population has been classified, crossover and mutation are performed on the population.

In the next generation, the population has solutions according to the dummy fitness values assigned to the successive fronts. Since individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population, which was intended to search for nondominated regions or Pareto-optimal fronts. This results in quick convergence of the population toward nondominated regions, while sharing helps to distribute individuals over the nondominated region.

### 3.9.4 Sharing in Genetic Algorithm

Simple GA's have been criticised for sub-par performance on multi-modal functions. They have been criticised for so-called premature convergence where substantial fixation occurs at most bit positions before obtaining sufficiently near optimal points. To overcome these maladies, Goldberg and Richardson (1987) has proposed a cure borrowed from nature. The remedy causes the formation of niche-like and species-like subdivision of the environment and population through the imposition of “sharing functions”. These sharing functions help mitigate unbridled head-to-head competition between widely disparate points in a search space. This reduces the competition between distant points in a search space, which leads to more diverse population and more considered (and less premature) convergence.

As mentioned in the previous section, NSGA is similar to a simple GA except for the classification of nondominated fronts and the *sharing* operation. A sharing function is used to determine the degradation of individual's payoff due to a neighbour at some distance as measured in some similarity space. The distance  $d_{ij}$  can be defined in two possible ways (Deb

and Srinivas, 1995) (1) *Phenotypic distance* which is measured based on the difference in the decoded problem variables and (2) the *genotypic distance* which is measured based on the difference in the coded problem variables (in the gene space) between two individuals  $i$  and  $j$ . The sharing of fitness in NSGA is achieved by calculating a sharing function value  $Sh(d_{ij})$  between two individuals  $i$  and  $j$  in the same front, using the following formula (Deb and Goldberg, 1989)

$$Sh(d_{ij}) = \begin{cases} 1 - (d_{ij} / \sigma_{share})^2, & \text{if } d_{ij} < \sigma_{share} \\ 0, & \text{otherwise} \end{cases}$$

where  $d_{ij}$  is the phenotypic distance allowed between individuals identified by  $i$  and  $j$ ,  $\sigma_{share}$  is the maximum phenotypic distance allowed between individuals that would become member of a niche (There exists another type of sharing, known as genotype sharing, where the sharing function is evaluated using the number of different coding bits between the two individuals (Deb and Goldberg, 1989) Phenotype sharing has been shown to be superior to genotype sharing for the effective operation of NSGA (Deb and Goldberg, 1989)

A niche (akin to biological niches formed by organisms by resource sharing) is a stable, non-competing sub-population of individuals surrounding the important peaks in the fitness landscape in the search space (Srinivas, 1998). A parameter *niche count* is calculated for each individual  $i$  by adding already calculated sharing function values ( $Sh_{ij}$ ) of the individual  $i$  with all other individuals  $j$  coexisting with it on the current nondominated front. Finally, the shared fitness value of each individual  $i$  is calculated by dividing its dummy fitness value by its niche count.

## **Chapter 4**

# **INJECTION MOLDING**

Injection molding process is a complex but highly efficient means of producing a large variety of thermoplastic products particularly those with high volume production requirements, tight tolerances and complex shapes. The final product quality of injection molded part must include final material properties as well as structural and aesthetic considerations.

The Product quality in injection molding is a function of the material used, the mold design and the processing conditions. The important processing conditions during the filling phase are the mold temperature, melt temperature and filling time. This chapter starts with an overview of injection molding, in which injection molding process is discussed. Different aspects of mold design are discussed, and the characteristics of the plastic material are mentioned. Also discussed is how the characterisation of the process parameters is done. The chapter concludes with the explanation of how NSGA can be applicable to the optimisation of injection molding.

## **4.1 INTRODUCTION**

Injection molding is one of the most common and versatile operations for mass production of complex plastic parts with excellent dimensional tolerance. It requires minimal or no finishing or assembly operations. Injection molding is a cyclic process of forming plastic into a desired shape by forcing the plastic material under pressure into a cavity. The shaping is achieved by cooling (for thermoplastics) or by a chemical reaction (for thermosets). Injection molding is one of the important processes for producing the plastic products. Approximately 32%

percent by weight of all plastics processed go through injection molding machines (CMOLD design guide, 1994) Historically, the major milestones in the development of injection molding include the invention of the reciprocating-screw machine and the application of computer simulation to the design and manufacture of plastic parts

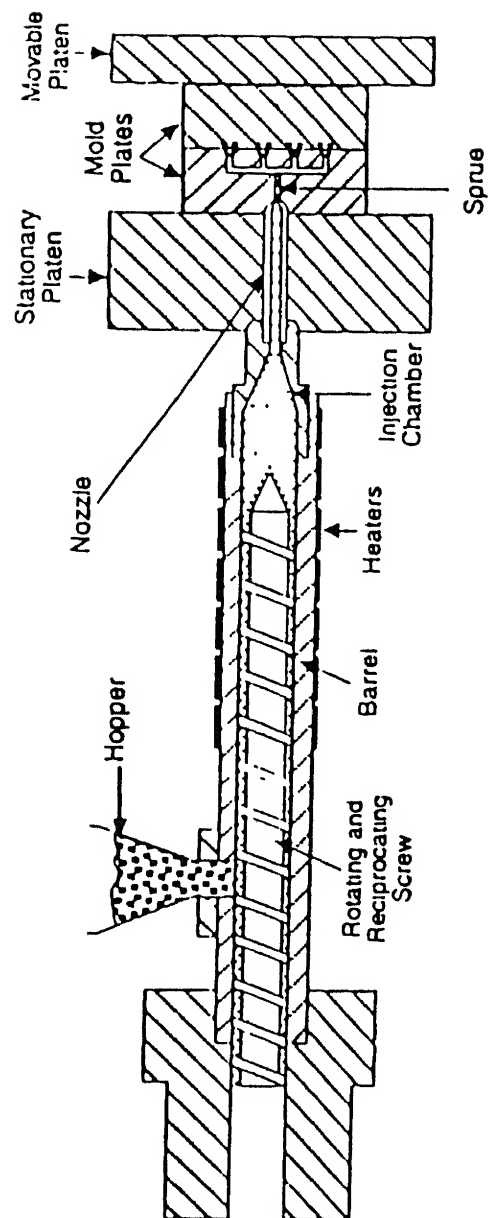
Since its introduction in the early 1870's, the injection molding machine has undergone significant modifications and improvements In particular, the invention of the reciprocating screw machine has revolutionized the versatility and productivity of the thermoplastic injection molding process Apart from obvious improvements in machine control and machine functions, the major development for the injection molding machine is the change from a plunger mechanism to a reciprocation screw The inherent advantage of using reciprocating machine over plunger-type machine is, it can plasticize the material more quickly and uniformly with its rotating motion

#### **4.1.1 The Injection Molding machine**

A typical injection molding machine consists of the following major components

- Injection system
- Hydraulic system
- Mold system
- Clamping system
- Control system

The injection system consists of a hopper, a reciprocating screw and barrel assembly, and an injection nozzle (Figure 4 1). This system confines and transports the plastic as it progresses through the feeding, compressing, degassing, melting, and injection stages Material is supplied to the machine in the form of small pellets or chips through the hopper throat into the



**Figure 4.1** The reciprocating-screw injection machine.

barrel and screw assembly The barrel of injection molding machine supports the reciprocating plasticising screw The barrel is heated by the electric heater bands The reciprocating screw is used to compress, melt (by pressure) and convey the material into the mold cavity The reciprocating screw consists of three zones the feeding zone, the compressing (or transition zone), and the metering zone While outside diameter of the screw remains constant, the depth of the flights on the reciprocating screw decreases from the feed zone to the beginning of the metering zone These flights compress the material against the inside diameter of the barrel, which creates viscous (shear) heat. This shear heat is mainly responsible for melting the material The heater bands outside the barrel help maintain the material in the molten state The nozzle connects the barrel to the sprue bushing of the mold forms a seal between the barrel and the mold. The temperature of the nozzle should be set the material's melt temperature or just below it

The injection mold system consists of tie bars, stationary and moving platens, as well as molding plates (bases) that house the cavity, sprue and runner systems, ejector pins, and cooling channels (see Figure 4.1) The injection mold is essentially a heat exchanger in which the molten thermoplastic solidifies to the desired shape and dimensional details defined by the cavity

The hydraulic system on the injection molding machine provides the power to open and close the mold, build and hold the clamping tonnage, turn the reciprocating screw, drive the reciprocating screw, and energize ejector pins and moving mold cores A number of hydraulic components are required to provide this power, which include pumps, valves, hydraulic motors, hydraulic fittings, hydraulic tubing, and hydraulic reservoirs

The control system provides consistency and repeatability in machine operation. It monitors and controls the processing parameters, including the temperature, pressure, injection speed, screw speed, and position, and hydraulic position. Process control has a direct impact on the final part quality and the economics of the process. Process control systems can range from a simple relay on/off control to an extremely sophisticated microprocessor-based, closed-loop control.

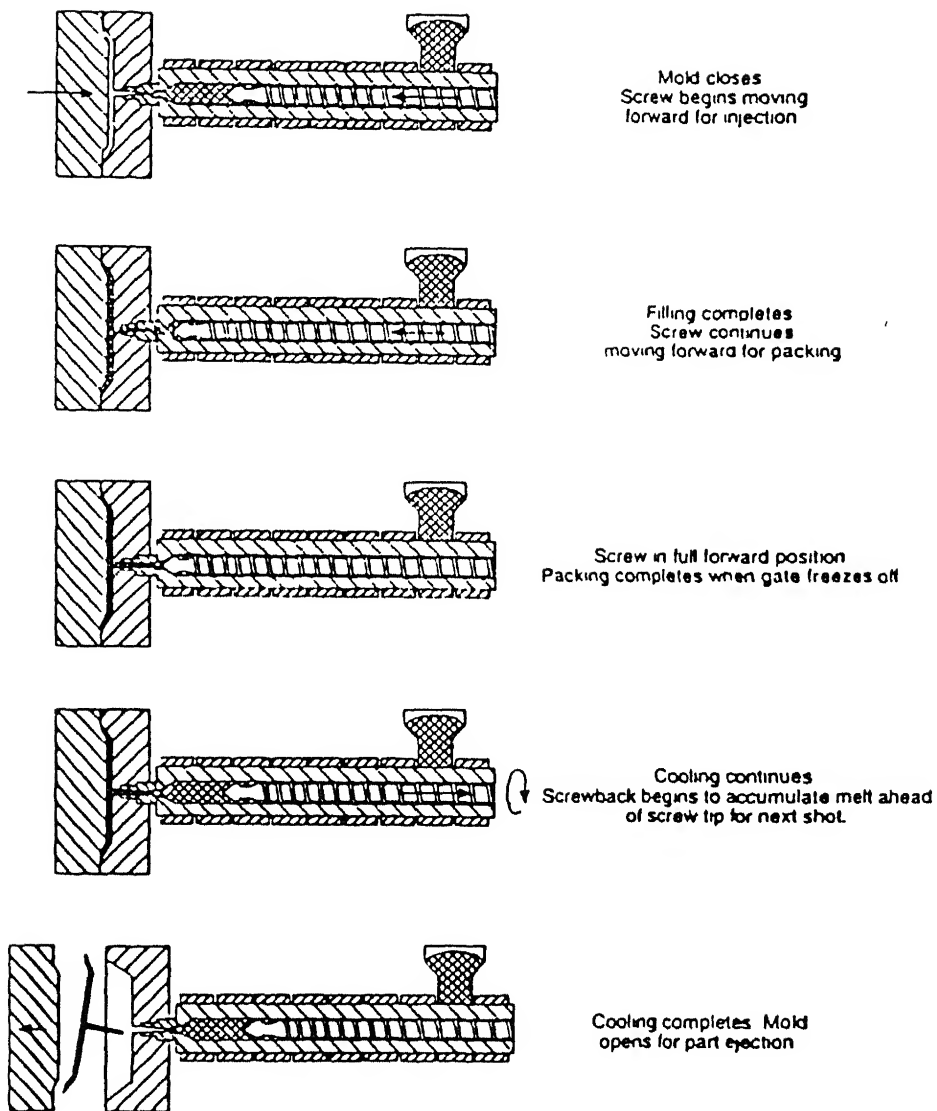
The clamping system opens and closes the mold, supports and carries the constituent parts of the mold, and generates sufficient force to prevent the mold from opening. Clamping force can be generated by a mechanical (toggle) lock, hydraulic lock, or a combination of these two basic types.

Clamping tonnage and shot size are commonly used to quickly identify the size of the injection molding machine for thermoplastics. Other parameters include injection rate, injection pressure, screw design, mold thickness, and the distance between the bars. The major auxiliary equipment to an injection molding machine includes resin dryers, material-handling equipment, granulators, mold-temperature controllers and chillers, part-removal robots, and part-handling equipment.

#### **4.1.2 Process Cycle**

Injection molding is a cyclic process. During the injection molding process, the machine undertakes a sequence of operations in a cyclic fashion. The basic injection molding machine operations, shown in Figure 4.2 (CMOLD design guide, 1994) are as follows:

- the cavity fills as the reciprocating screw moves forward, as a plunger,
- the cavity is packed as the screw, continuously moves forward,



**Figure 4.2 The basic injection molding machine operations**

- the cavity cools as the gate freezes off and the screw begins to retract to plasticize material for the next shot,
- the mold opens for part ejection, and
- the mold closes and the next cycle begins

A process cycle is one complete operation of an injection molding machine. It encompasses the mold closing, filling, packing, cooling, mold opening, and ejection stages. Typical process cycle time varies from a few seconds to tens of seconds, depending on the part weight, part thickness, material properties, and the machine settings specific to a given process.

## 4.2 Molds

The success of accurately producing the desired shape by injection molding process depends on the proper functioning of the molding machine, the processing material and ultimately the mold used. Injection molding is usually adopted for producing thin walled components in large quantities at a time. So the importance of an optimal mold design is of paramount importance. The mold design depends on the product to be made and the machine on which the mold is to operate. The following characteristics are to be considered in deciding the type of mold design for a particular injection molding process:

- 1 The presence or absence of external or internal undercuts on the part to be molded
- 2 The type of gating and means of degating
- 3 The type of ejection used
- 4 The manner in which the product is released from the mold

The various aspects that one has to take into account in mold manufacturing are as follows:

- 1 Gate location

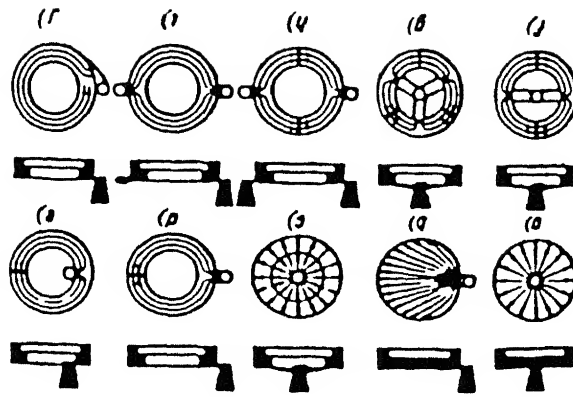
- 2 Mold type selection
- 3 Cavity placement
- 4 Gating type
- 5 Ejector system
- 6 Mold material selection

#### 4.2.1 Gate location

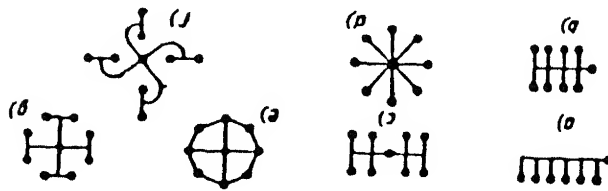
The basic principle of moldflow is that if the material flows without any hindrance to each extreme point in the mold then *weld lines, voids and incomplete filling can be avoided*. In this context, the location of the point from which the molten metal is poured plays a very important role. This entry point is known as the “gate”.

Molds that can either be of the single cavity type, i.e., producing one single part at a time or of the multi cavity type, i.e., producing more than one part at a time. Figure 4.3 (Crawford, 1988) shows the possible locations of the entry point for some representative single cavity molds. Figure 4.4 (Crawford, 1988) shows the possible locations of the entry point for some representative multicavity module.

The most natural and efficient entry point is the centre of the mold in case of single cavity molds as shown in Figure 4.3 (a). In this case, the material has to cover the same distance in all directions in the mold cavity. This solution is the best even in case of multi cavity molds as shown in Figure 4.3 (c,d,g). For a side entry of the material, there is a danger of weld lines and incomplete filling shown.



**Figure 4.3** Possible gate locations for single cavity molds.



**Figure 4.4** Possible gate locations for multi cavity molds.

in Figure 4 3 (d,e) The possibility of incomplete filling increase in case of multi cavity molds. If an entry point other than the center of the mold is chosen, the material cools down considerably by the time the most distant cavity is reached as shown in Figure 4 4 (a,b). Also, the pressure required for filling the mold increase substantially.

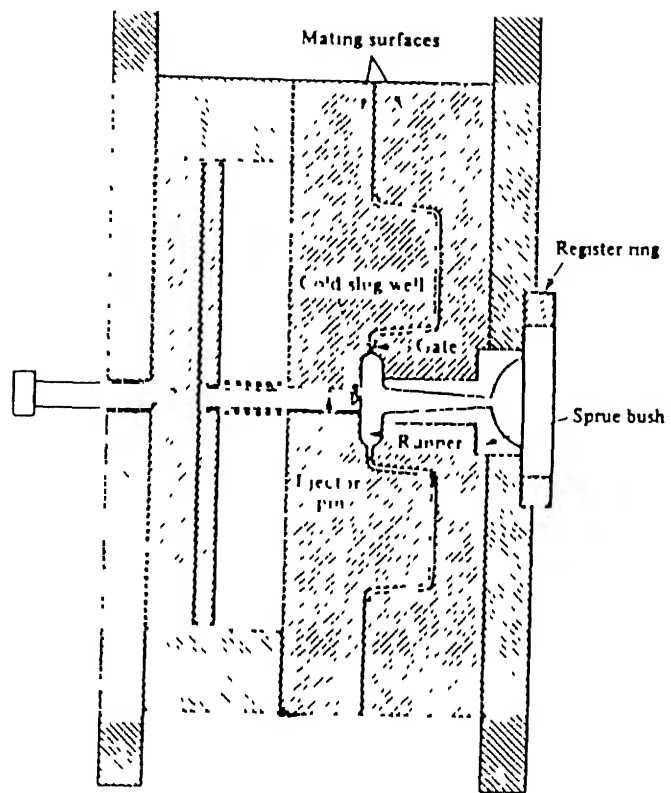
Hence, the location of the entry point or “gate” is important to have a defect free molded part. In case of molds with simpler shapes viz rectangular or circular, the problem of gate location is relative easy. The problem becomes complex in case of molds with shapes other than rectangular and circular. In such cases, the necessity of an optimal location of the gate arises. The location must be based on the geometrical features of the mold.

#### **4.2.2 Mold type selection**

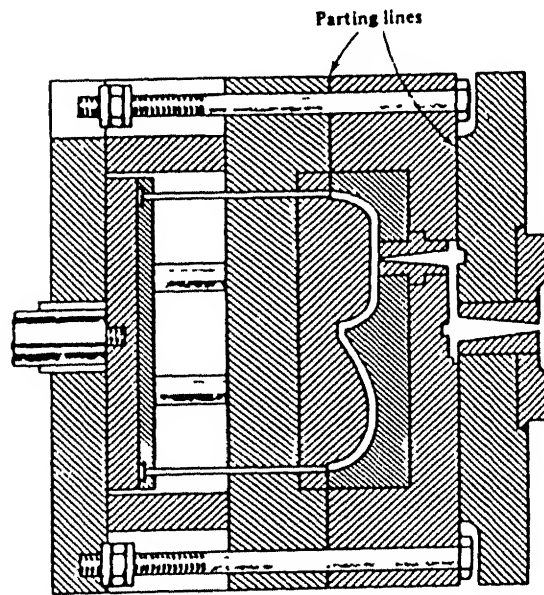
The type of mold to be used depends on the geometrical attributes viz shape and size of the final product. The type of mold may either be of the two plate mold type or the three plate mold type.

The two plate type is the simplest type of mold, comprising essentially of two die plates which carry the female cavity and the male punch respectively. Such types of molds are used for box or bowl type moldings. The three plate mold type has a third plate, generally known as the floating or centre plate in addition to the two plates as in two plate mold type. Three plate mold types are frequently used for the production of small or medium sized components. Figure 4 5 and Figure 4 6 show the two plate mold type and three plate mold type respectively.

Depending on the geometry of the part, the location of the gate and the machine on which it is to be used, a suitable selection of the type of mold is done.



**Figure 4.5 A two plate mold**

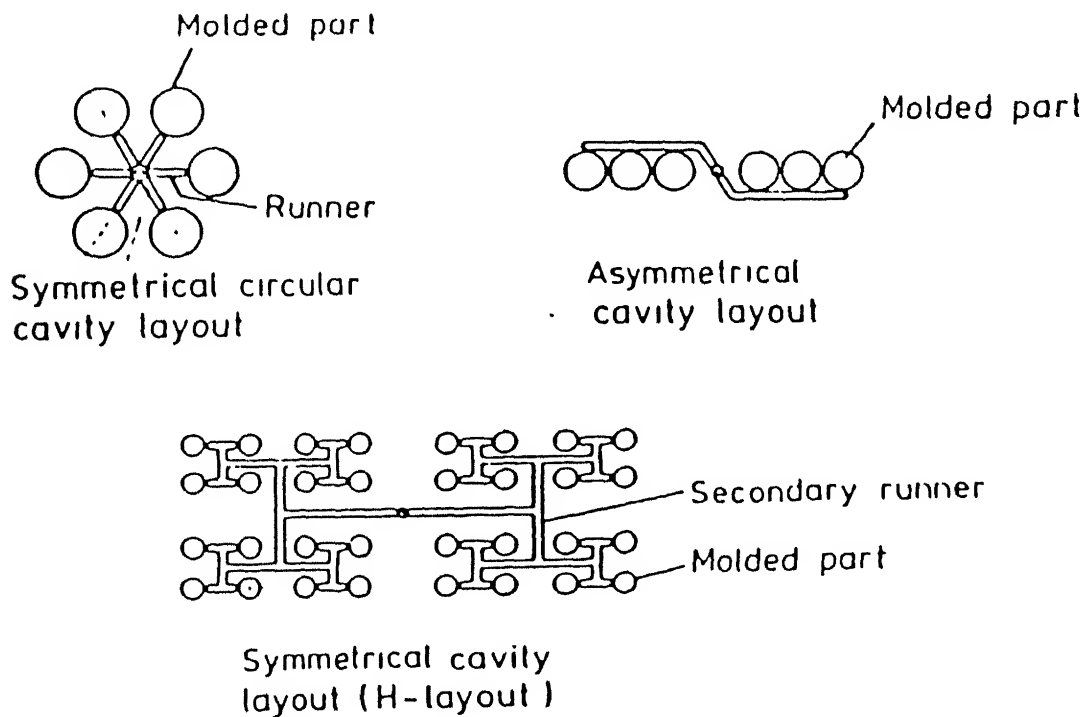


**Fig. 5.8 3-plate mould**

**Figure 4.6 A three plate mold**

### 4.2.3 Cavity placement and Gating type selection

The basic reason for the employment of multiple cavities is to obtain a greater output in a given time. The placement of these cavities has a considerable effect on the final product characteristics. The prominent types of cavity placements are star, asymmetrical and symmetrical. Depending on the location of the gate and the machine parameters of clamping force and platen size, a proper arrangement of cavities is done. Figure 4.7 shows the layouts possible with the associated runner system for injection molds.



**Figure 4.7 Cavity Layouts in injection molds**

The type of gating depends on the mold geometry and the use to which the final product might be put to. The selection of the gating system is to be done from the following types of gates: direct, pinpoint, film, rectangular.

#### 4.2.4 Ejector System Selection and Mold Material Selection

Injection molded compounds exhibit a certain amount of shrinkage, i.e., in a cooled condition the volume is somewhat smaller than in a heated condition. If parts with accurate dimensions are needed, allowances must be made for this shrinkage when establishing the dimensions for the cavities. Shrinkage also causes the molded part to sit tight on the cores. The parts are ejected after they have cooled down. As a result, special ejection methods like pins, stripper rings, air and slides are to be appropriately matched with the part geometry and machine on which the ejector system works.

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Various materials have been reported to be used for mold manufacturing and their selection mainly depends on the process of manufacturing the mold, i.e., whether a conventional method like milling is used or a conventional method like EDM is used. A suitable selection can be made depending on whether the material in question is to be used to make the base, inserts, plates or cores. The usual materials are heat treated steels, plain tool steels, nitriding steels.

#### 4.3 Plastics

Plastics are one group of polymers which are built from relatively simple units called monomers (or mers) through a chemical polymerisation process. Processing polymers into end products mainly involves a physical change (for thermoplastics) or a chemical reaction (for thermosets). The following ASTM definition of plastics is widely accepted (Watson, 1994).

*A material that contains as an essential ingredient one or more polymeric substances of high molecule weight. It is solid in its finished state and, at some stage in its manufacture or processing, can be shaped by flow into finished articles. Synthetic*

*fibres, textiles, natural and synthetic rubbers, adhesives and paints which may in some cases comply with this definition, are not considered to be plastics*

The basic structure of a polymer molecule may be visualized as a long chain of repeating units, with additional chemical groups forming pendant branches along the primary “backbone” of the molecule. The structure arrangement, size, and chemical constitution of the polymer molecule have a direct influence on its physical and chemical properties. In addition, the macromolecular nature of the plastics implies that their material properties may also be dependent on the mechanical and thermal history that the materials experience during processing. For example, the viscosity (which indicates the material’s resistance to flow) of a polymer melt increases with increasing molecular weight, but decreases as temperature increases. Further, the aligned molecular orientation that results from strong shear exerted on the material also reduces the viscosity of the polymer melt. The physical and mechanical properties, as well as the cost of polymers, can be modified by blending a number of polymers or by compounding polymers with other materials or reinforcing agents.

### **4.3.1 Classification of Plastics**

Based on the type of chemical reaction (polymerisation) that links the molecules together, plastics are classified as either thermoplastics or thermosets.

#### **4.3.1.1 Thermoplastics**

Thermoplastics typically have high molecular weights resulting from a high degree of polymerisation. The long molecular chain, either linear or branched, has side chains or groups that are not attached to other polymer molecules. As a result, thermoplastics can be repeatedly

softened (or hardened) by an increase (or decrease) in temperature. This type of phase change without a chemical reaction permits the recycling of thermoplastic scraps such as the trimmed-off runners and sprues from injection molding. Although thermoplastics are recyclable, it is very likely that a small degree of chemical change (e.g., oxidation, thermal degradation) takes place during processing, and therefore the properties of recycled polymers may not be equivalent to those of the virgin polymer.

Thermoplastics account for more than 70% of all polymers produced. Among thermoplastics, the commodity resins, are high-density polyethylene (HDPE), low-density polyethylene (LDPE), polypropylene (PP), polystyrene (PS), and polyvinyl chloride (PVC). These materials constitute 90% of all thermoplastics.

### **4.3.2 Thermosets**

Cross-linking is a chemical process in which chemical bonds form among molecules of thermosetting materials, resulting in an interconnected network. The cross-linking process is the principle difference between thermoplastics and thermosets. Prior to molding, the chain-like structure of thermosets are similar to thermoplastics. During processing, thermosets polymerize (react or cure) with the activation of heat and/or a chemical means into a cross-linked microstructure. Once the reaction is completed, the polymer chains are bonded (cross-linked) together to form a three-dimensional network. These cross bonds among molecules prohibit the slippage of individual molecular chains. Consequently, a thermoset becomes an infusible and insoluble solid and cannot be re-softened and reprocessed through the application of heat, without degrading some linkages. Typical examples of thermosets are, phenol-formaldehyde, melamine-formaldehyde, urea-formaldehyde and epoxies.

**Table 4.1 Comparison of structures and properties of thermoplastics and thermosets**

Material	Thermoplastics	Thermosets
Microstructure	Linear or branch molecules No chemical bonds among the molecules	Cross-linking network with chemical bonds among molecules after the chemical reaction
Reaction of Heat	Can be re-softened (physical phase change)	Cannot be re-softened after cross-linking without degradation
General Properties	Higher impact strength. Easier processing Better adaptability to complex designs	Greater mechanical strength Greater dimensional stability Better heat and moisture resistance.

#### **4.4 Processing Parameters**

The mechanical and physical properties of a molded part do not depend solely on the chemical constitution of its material. The processing conditions exercise a considerable influence on the strength, distortion, dimensional stability, surface finish and tendency to stress cracking. These factors that represent the part quality are not apparent externally, but are reflected by the structure of the part.

The variables that affect the Injection molding process can be categorised into geometrical and operational considerations. Geometrical considerations such as gate location affects the part quality by affecting the temperature, pressure and shear stress by alternating the balance and direction of the material flow.

Operational considerations such as melt temperature, mold temperature and fill time affect part quality by changing the conditions under which the mold is filled. The operational considerations are said to make up the Injection molding conditions. Also the selection of an appropriate cooling system is of immediate importance since an improperly selected cooling system can result in hidden stresses in small parts, distortion in larger parts with relatively thin walls and even crack formation. Hence, an approach to determine the suitable cooling system and the optimal combination of temperature, pressure and time is needed.

#### **4.4.1 Characterisation of the Process**

A number of process parameters may affect the formation of a good molded part. However, the major ones are

- Pressure
- Temperature
- Time

In the context of characterisation of the process, the parameter pressure is usually referred to as the cavity pressure. The distribution of the cavity pressure at different stages of the molding process as it proceeds with time immensely influences the quality of the molded part. Figure 4.8 (Johannasari, 1983) shows the cavity pressure profile over time.

The information available from the cavity pressure curve can be divided into three stages.

- 1 Filling of the cavity ( Injection stage)
- 2 Compression of the melt ( Compression stage)
- 3 Holding the solidifying material under pressure (Holding stage)

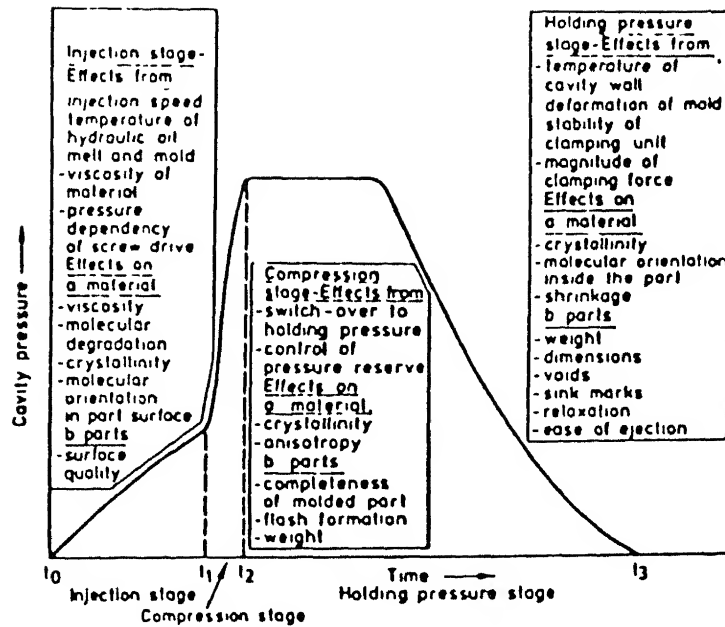


Figure 4.8 Cavity pressure profile over time

These three stages can be related to *quality criteria effects*. The injection pressure has the function of overcoming the flow resistance from the nozzle to the cavity. The compression pressure plays a significant role in avoiding defects like shrinkage and voids. The holding pressure is responsible for maintaining an uniform pressure. However, as the mold is solidifying, the pressure decreases. The major effects of an improperly maintained holding pressure are voids, sink marks and dimensional instability.

The most important processing conditions during the filling phase are the *mold temperature*, the *melt temperature*, and the *filling time* (Pandelidis and Zou, Part-I, 1990). The selection of correct molding conditions in the injection molding process is a non-trivial task. An increase in melt temperature causes a decrease in melt viscosity, which results in reduced pressure requirements and reduced stresses. On the other hand, high melt temperature may increase the possibility of material burning and will also increase cooling time. Increasing the mold

temperature reduces heat losses, and the maximum temperature difference at the end of the filling phase may be reduced. However, a high mold temperature increase cooling time. Short fill time require higher pressure because a higher flow rate requirement, resulting in higher shear rate and shear stress. Then, if the fill times are too long, pressure will increase because the plastic temperature decreases and the viscosity increases. It is clear from above discussion that some optimisation to balance the conflicting processing parameters is required to produce a good quality product (Pandelidis and Zou, Part-II, 1990).

The time for one single run usually is called the *cycle time*. The cycle time consists of filling time, dead time and cooling time. As cycle time is dependent on the filling time and rate of cooling, faster rate of filling and cooling will result in increase of production rate. For this, the cooling system must provide the most uniform possible temperature distribution in the mold so that cooling is uniform and homogeneity in microstructure results.

#### **4.5 Quality Measures and Processing parameters optimisation**

It is required to develop quantitative measures of the part quality since the ultimate goal is to improve the final product characteristics. The term *quality* may be referred to many product properties such as mechanical, electrical, optical or geometrical. There are two types of part quality measures: direct and indirect (Pandelidis and Zou, Part-I, 1990).

A model that predicts the warpage from flow simulation results would be characterised as a direct quality measure. In contrast, an indirect measure of quality is a quantity that is correlated but does not produce a direct estimate of that quality. However, direct quality measures are usually more expensive to evaluate than indirect quality measures. Prediction of warpage is too time consuming. So, an alternative measure is adopted.

Many factors affect the quality of the final part. One of the most damaging causes is due to warpage. Warpage in the part occurs due to

- 1 Uneven temperature distribution and uneven cooling in the part
- 2 Inhomogeneity of part density
- 3 Anisotropy in thermal shrinkage
- 4 High unbalanced residual stress distribution

The major causes of material degradation are high temperature (burning) and high shear rate.

The indirect quality measures are those related to warpage and material degradation. Instead of using finite element stress and thermal analysis to predict warpage and material degradation directly, we quantify the major causes of warpage and material degradation as described in the subsequent sections. For optimisation, we restrained ourselves with quality measures which are controllable at the filling phase. The packing and cooling phase must also be considered when full design is implemented.

#### **4.5.1 Temperature Difference**

Temperature difference is a measure of the temperature distribution uniformity in the mold once it has been filled by the material. The temperature used here is the average temperature. The amount of shrinkage that a plastic undergoes during cooling is a function of its temperature (Pandelidis and Zou, Part-I, 1990). All other factors being equal, a nonuniform temperature distribution will cause *differential shrinkage* and, therefore, *warping* in the cooling process. Ideally, the temperature at each point should be same at the end of filling. This ensures the non uniform shrinkage due to difference in temperature will be eliminated. Unfortunately, this rarely occurs. Heating occurs in the flow because of frictional and shearing effects. At the same time, cooling takes place at the plastic mold interface. Thus, in general, at

the end of fill stage there will be a nonisothermal temperature distribution throughout the part. In a finite difference simulation, there will be discrete temperature differential. The subsequent differential shrinkage that occurs will induce residual stresses causing warpage and other detrimental short and long-term effects.

The parameter  $T_d$  has been defined to quantify the severity of the temperature difference.  $T_d$  is simply the difference between the maximum and minimum temperature at the end of fill over entire part which are available in simulation results. This provides a reliable measure of uniformity of temperature and can be represented mathematically as follows:

$$T_d = T_{\max} - T_{\min} \quad (4.1)$$

where,

$T_{\max}$  = maximum temperature in the mold

$T_{\min}$  = minimum temperature in the mold.

#### 4.5.2 Pressure

Another cause of warpage is the existence of non-uniform pressure in the mold after it has been filled. During the cooling phase the areas with relatively high pressure will shrink less than areas of lower pressure.

There will be pressure losses during the filling stage. These losses are the result of the continual shearing and friction that occurs as the polymer melt is forced into the mold. Ideal conditions will exist if in each part of the mold has the same pressure gradient. Higher pressure will result in *higher shear rate and shear stresses which will cause warpage, mechanical sticking and flash* (John Bown, 1982).

The parameter  $P_{\max}$  has been defined to quantify the severity of pressure distribution.

### 4.5.3 Optimisation

Process Variable	Effect	Quality Problems
Melt temperature	Increasing the melt temperature causes a decrease in melt viscosity, which results in reduce pressure requirements and reduced stresses. On the other hand, high melt temperature may increase the possibility of material burning and will also increase cooling time.	Material degradation, and Short shot
Mold temperature	Increasing the mold temperature reduces heat losses, and the maximum temperature difference at the end of filling phase may be reduced. High mold temperature is required for improved part appearance is a concern. A higher mold temperature produces higher gloss and more crystallization. However, a high mold temperature increase cooling time.	But if rapid curing takes place the moldings are liable to exhibit porosity in the thicker sections and some burning may take place. Flow marks, warping and excessive shrinkage may occur with too rapid curing.
Fill time	Short fill time require higher pressure because a higher flow rate requirement, resulting in higher shear rate and shear stress. Then, if the fill times too long, pressure will increase because the plastic temperature decreases and the viscosity increases.	Warping, Excessive shrinkage and flashing

From the discussion above we can say that, the quality of the injection molding part is affected by the various factors of mold design, filling phase, cooling phase and packing phase. In this study we are considering the parameters related to the filling phase i.e., processing conditions that effect the quality of the injection molding part. From the discussion above it is clear that the process parameter optimisation of the injection molding part is a multiobjective optimisation problem. As the objectives are conflicting (discussed in section 4.4.1), we can apply NSGA for solving the problem.

## Chapter 5

### MOLDING SIMULATION EXPERIMENTS

Plastics are an increasingly popular material for making parts in many industries including automotive, computer and consumer. The injection molding production process, a convenient way to make plastic parts, is nevertheless complex and extremely application-dependent. Previously, not all plastic parts could be analysed before production because of the time and expertise needed to undertake a simulation of the process before actual production began. This resulted in frequent and expensive part redesign and mold rework.

But the situation is changed, it has been now recognised that computer-aided engineering (CAE) including process simulation enhances engineers' ability to handle all aspects of plastic injection molding process, benefiting productivity, product quality, timeliness, and cost. The process behaviour predicted by CAE can help novice engineers overcome the lack of previous experience and assist experienced engineers in pinpointing factors that may otherwise be overlooked.

Keeping in view the demands of the plastics industry people to giants in the injection molding software business, namely MOLDFLOW and CMOLD, have developed two simulation software called PART ADVISER and 3DQUICKFILL respectively. Both these software's now bring the benefits of process simulation directly to the desk of the product designer. In the present study both these software's are used for generating the data required for the optimisation of process parameters of injection molding. Discussed in Chapter 4.

Both the software's accept solid geometry models from CAD software, built from any of the popular CAD systems such as Pro/Engineer, IDEAS, or Unigraphics etc., CMOLD's 3DQUICKFILL takes the injection molded part design of the stl format whereas Partadviser accepts the part in mpa format

## **5.1 C-MOLD 3D QUICKFILL**

### **5.1.1 Introduction**

C-MOLD 3D Quickfill (Quickfill) is a desktop plastics CAE software tool that helps part designers, mold designers, and molders incorporate engineering decisions and manufacturability considerations into the earliest stages of product development. Vendors of CMOLD claim that the information provided by Quickfill helps designers test feasibility, manufacturability, cost, and performance concerns against real-life constraints. As mentioned, C-MOLD 3D Quickfill accepts solid geometry models from CAD software's like Pro-engineer, I-DEAS, Unigraphics etc, in stl (stereolithography) format.

### **5.1.2 Procedure to start process simulation on the C-MOLD 3D Quickfill**

#### **Software**

The following are the steps that one has to follow to run the simulation on Quickfill

1. **Start the Quickfill :** Quickfill runs both in the Windows and Unix environments
2. **Open your solid model :** Quickfill accepts solid geometry from any CAD product, saved in the STL ( stereolithography) format. One can import an STL file or can open a surface mesh in CMOLD FEM format
3. **Control the view :** Quickfill provides the controls so you may position the model for the best view, using the various control buttons.

### 5.1.3 Features of CMOLD 3D Quickfill

- 1 For the process conditions used for the simulation, Quickfill gives whether the part either short or it doesn't and Quickfill will show you exactly where the short shot occurred. If your part short shots, Quickfill tells you the remedy options. If your design requires excessive injection pressure or melt temperature, it tells what can be done. It even tells you when, and by how much, the part's thickness can be reduced and still be manufactureable.
- 2 Quickfill supplies the simulation results vital to knowing why some problem exists. Simulation results show how the four variables of injection molding (material, part, mold and machine) influence part quality.
- 3 For parts with multiple gates, mold designers would like to know how good each gate is performing. Quickfill tells you the % cavity filled through each gate. This allows you to strategically remove the under-performing gates and assist over-performing ones.
- 4 Using the simulation output of molecular and fiber orientation you can significantly improve part strength in critical areas (especially in the vicinity of weldlines). Quickfill helps you design for optimal performance. Part warpage can be minimised by selecting gate locations which balance the filling of the mold cavity.
5. In the Design advice given by Quickfill after each simulation, includes the injection pressure and machine clamp force tonnage required to mold the part, as well as suggestions for correcting or improving the design. For example, Quickfill tell you whether part thickness can be reduced, and by roughly what percentage it can be reduced, while still producing a part that will fill. Quickfill will also tell you if the variation in part thickness is large, or if it is too large.

6 Quickfill shows the design specifications used for the simulation. The specifications and calculated results include

- the resin selection and the Melt mass-flow rate (MFR)

MFR is a world-wide industry standard that can be thought of as a measure of how easily the melt can flow. MFR, is an ISO standard, is identical to the melt-flow index (MFI), an ASTM standard.

- the machine clamp force and shot size required for the part

Shot size is a measure of an injection molding machine's capacity. The measurement is the product of the area of the screw (ram) and the maximum travel that it can achieve.

- machine setup information, including the filling and cooling time, the required injection pressure and the melt and mold temperatures
- Part information including the part weight and projected area of a single cavity, the clamp force required for single cavity, the number of cavities, the parting plane, and the averaged part thickness and standard deviation of the part thickness. If the standard deviation is greater than 5%, the Design Advice report will warn you that the thickness variation is large; if it is greater than 10%, you will be warned that the thickness variation is too large.

#### 5.1.4 SIMULATION RUNS

In this section simulation results and some of the plots obtained from the Quickfill are presented with the help of one trial run. For showing the results obtained from Quickfill, a "tape" model is imported from the inbuilt database. LDPE plastic resin is chosen as the for this trial run. Default process conditions are used for the simulation run although if we want, we can change the process condition values such as mold temperature, melt temperature, number

of cavities and machine builder values of maximum injection pressure and maximum injection rate

Figure 5 1 shows the melt front advancement plot, this plot shows the filling pattern and whether the fill is balanced *Fill time* is noted from this plot

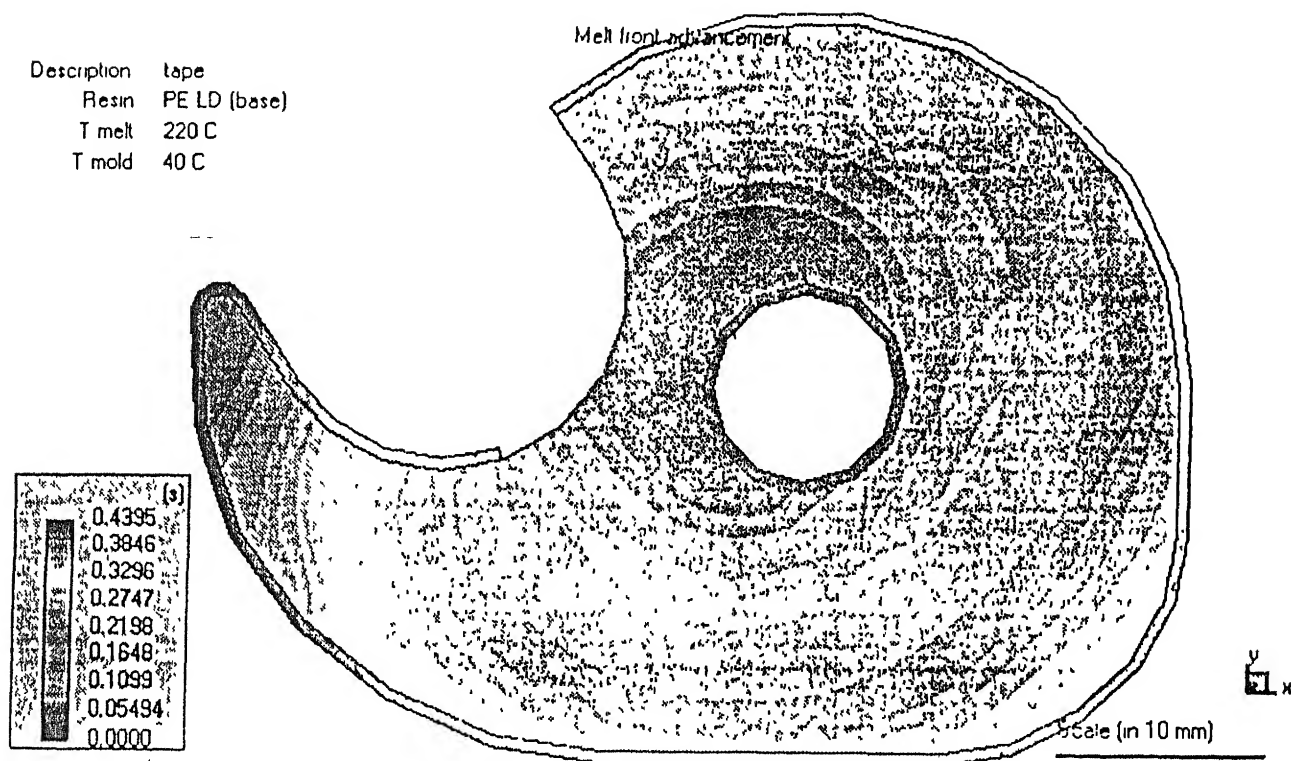


Figure 5.1 Melt front advancement plot

Figure 5.2 shows the pressure distribution by degree of greyness at the end of the filling, from this plot  $P_{max}$  can be noted Where  $P_{max}$  is equal to the injection pressure at the end of fill.

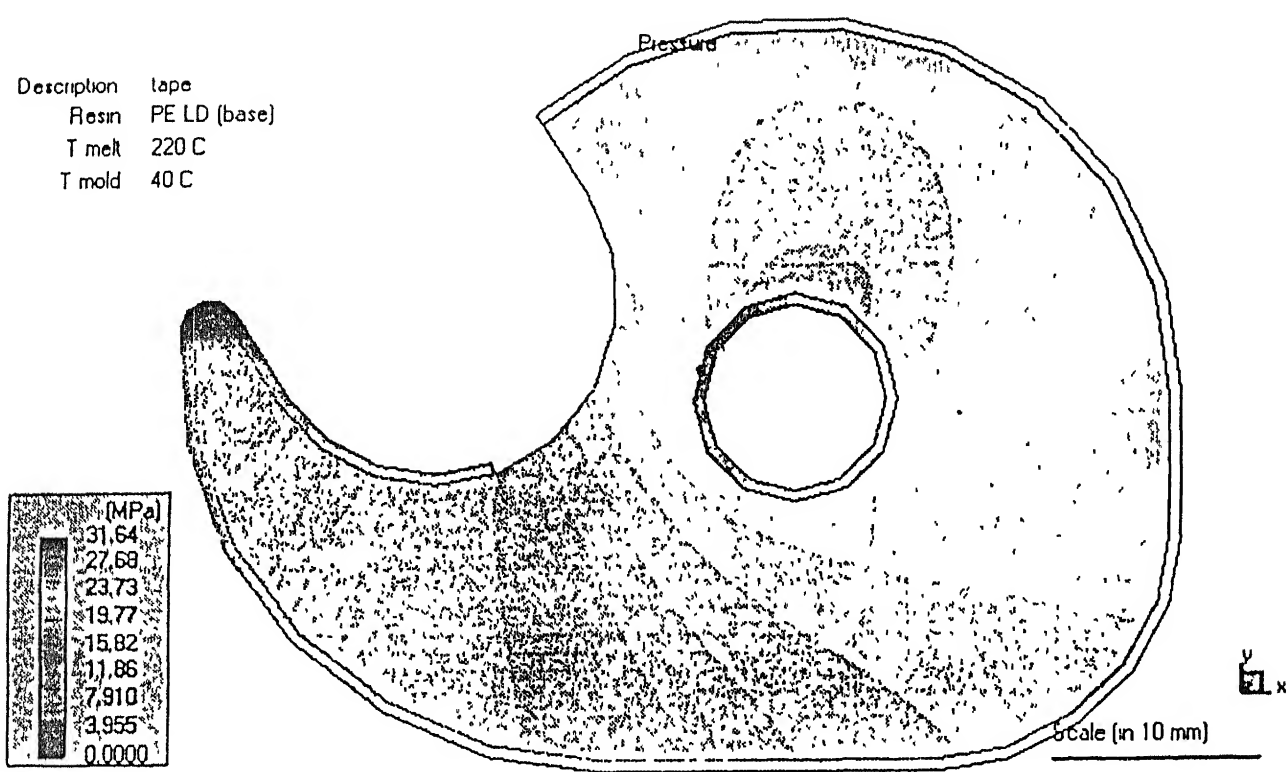


Figure 5.2    Pressure plot

Figure 5 3 shows the temperature plot Temperature plot shows by degree of greyness the spatial temperature variation across the part at the end of filling Greater the temperature variation on a part, the more potential there is for the part to warp From this plot *temperature difference* is noted.

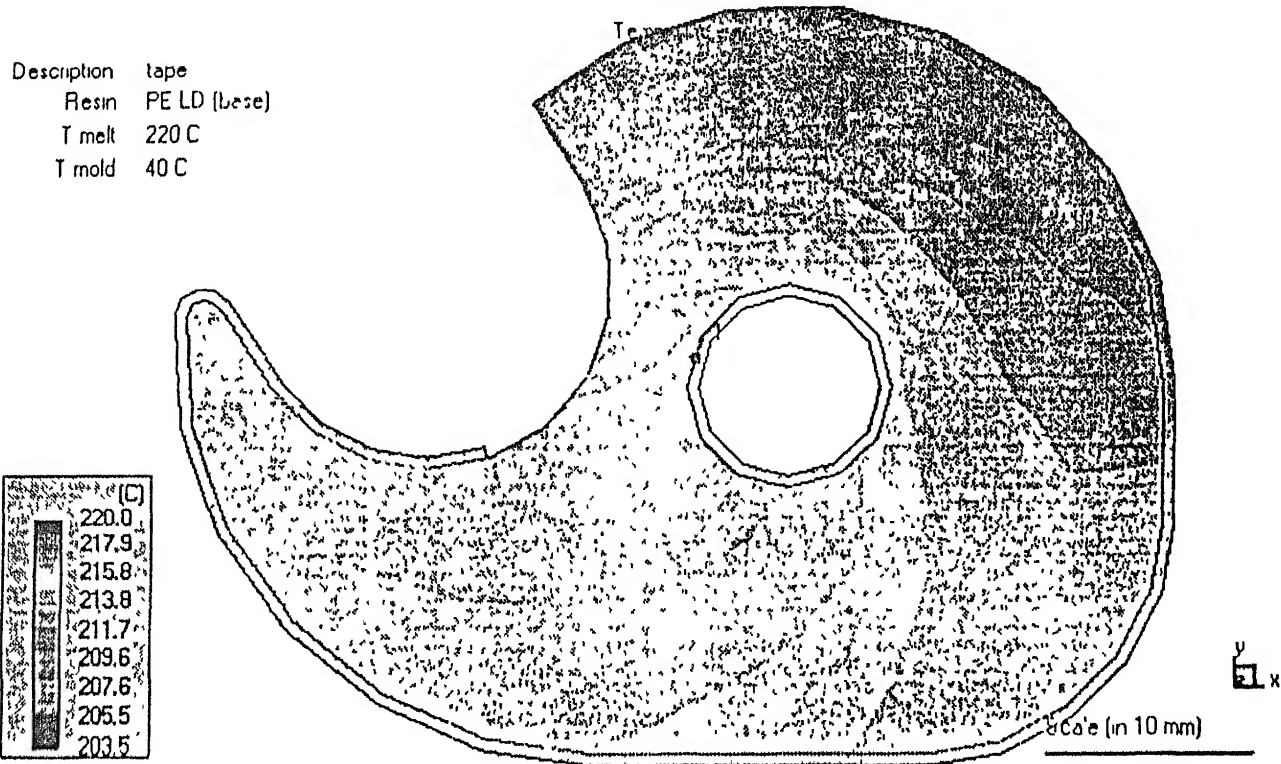


Figure 5.3 Temperature plot

Figure 5 4 shows the cooling time plot This plot shows how long it will take each area of the part to cool. The objective is to achieve the shortest possible cooling time while maintaining the integrity of the part. From this plot *cooling time* value is noted

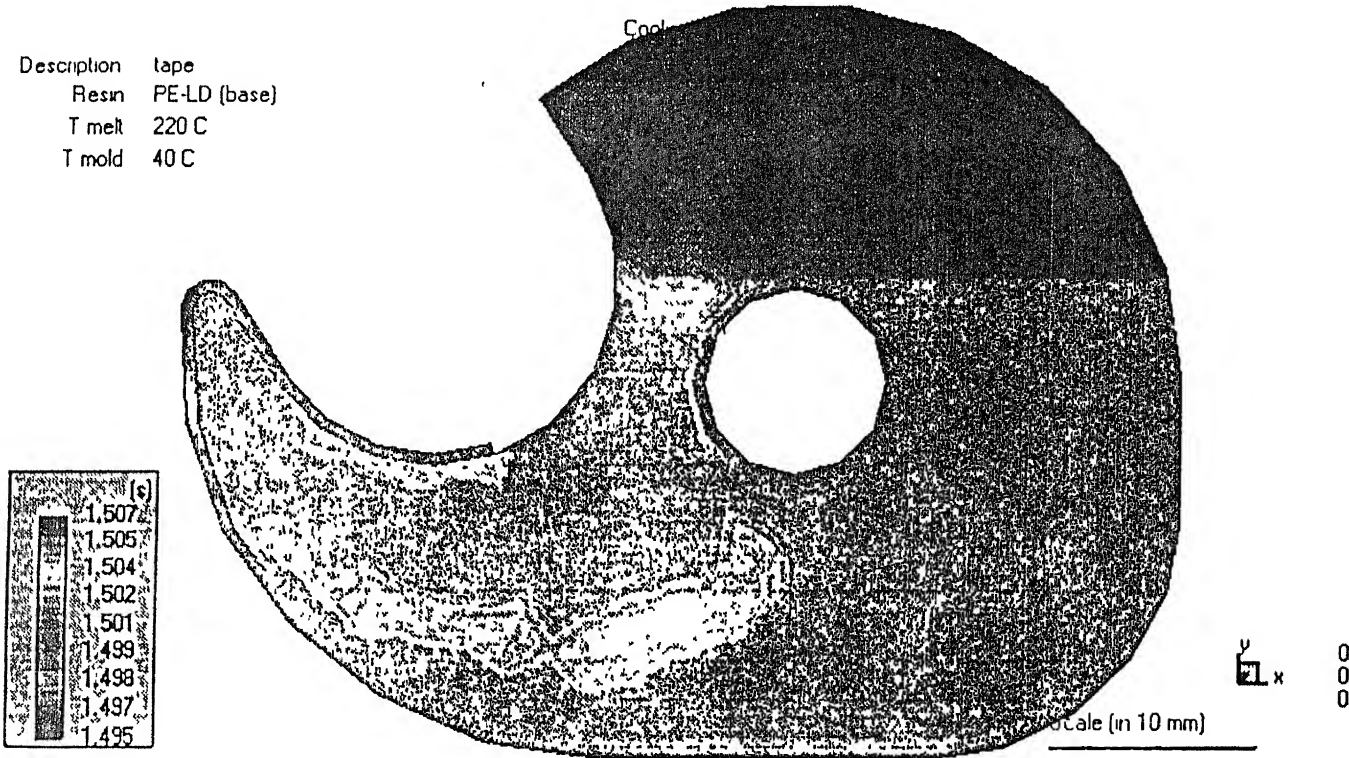


Figure 5.4    Cooling time plot

Figure 5.5 shows the *Design advice* given by the Quickfill for the above trial run. The advice includes the injection pressure and machine clamp force tonnage require to mold the part, as well as suggestions for correcting or improving the design

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C-MOLD 3D QuickFill 98.6 Design Advice.

The part(s) can be successfully filled with injection pressure of 32 MPa and clamp force tonnage of 12 ton(m).

The clamp force tonnage does not include the sprue/runner/gate systems. Inclusion of the sprue/runner/gate system will increase the required clamp force.

No resin degradation detected in the simulation.

The required injection pressure is in a reasonable range, or 18 % of the max injection pressure which can be delivered by a typical machine.

The part design has very uniform thickness.

The part thickness can be reduced by roughly 40 % and the part will still fill. Before reducing the thickness, however, you should consider the minimum thickness required for part strength. If you reduce the thickness, rerun 3D QuickFill for updated results

**Figure 5.5      Design Advice**

Figure 5.6 shows the *Design specifications* given by the Quickfill for the trial run,

Design Specifications

Date NOV03-98  
Time 07 37 34  
Name tape  
==== Resin specification ====

Polymer PE-LD (base)  
==== Machine specification ====

Required clamp force = 12.33 ton(m)  
Required shot size (GPS) = 11.48 g

The clamp force and shot size estimates do not include the sprue/runner/gate system

Inclusion of the sprue/runner/gate system will increase the required clamp force and shot size

Max injection pressure = 180.00 MPa  
Max injection rate = 26.61 cm<sup>3</sup>/s  
Machine performance = Good

==== Machine setup ====

Fill time = 0.44 s  
Cooling time = 1.50 s  
Injection pressure = 31.64 MPa  
Melt temperature = 220.00 C  
Mold temperature = 40.00 C

==== Part information ====

Single cavity part weight = 9.89 g  
Average part thickness = 1.19 mm  
Standard deviation of part thickness = 0.01 mm  
Single cavity projected area = 47.79 cm<sup>2</sup>  
Required clamp force for single cavity = 12.33 ton(m)  
Number of cavities = 1  
Parting plane is in XY plane  
100.0 % filled by gate # 1

**Figure 5.6      Design Specifications**

## 5.2 MOLDFLOW - PART ADVISER(3.0)

### 5.2.1 Introduction

Part Adviser is a simulation software of the Moldflow Corporation, one of the leaders in the process wide plastic simulation. This software, the vendor claims, enables the quick evaluation of each and every injection molded part design for “manufacturability”

The Part Adviser (PA) reads the model of your part created by a standard CAD package. PA analyses a CAD solid model directly and eliminates the need to translate geometry using an intermediate file or perform complex FEA meshing. Some inputs are required, including the material to be used, and the injection location.

### 5.2.2 Procedure to be followed to start a molding process simulation on PA

The following steps are to be followed to run the simulation on a PA.

- 1 **Open the PA from the desktop :** Open the PA after double clicking the icon from the desktop (PA is compatible to Windows95 and Windows NT 4.0)
- 2 **Open a model** PA accepts the solid models of the part made from the CAD packages such as I-DEAS, Pro-Engineer and Unigraphics etc., Open the model from stored database
- 3 **Select a polymer** All data related to polymer materials are stored in two locations, the standard database and local database. If an exact match of supplier and tradename cannot be found in the database, alternative materials may be selected using the polymer selection option and match criteria. Four criteria are used to search the database. They are listed in order of priority as below
  - polymer family

- melt flow index
- type of filler
- percentage of filler

If you provide the search data, the matches found and a window is dynamically updated, showing materials that match the criteria provided

4. **Manipulate the model** . There are number of tools available to rotate and manipulate the model in PA. These can assist in determining a best location for polymer injection to view results. Various tools available are “Pan the model”, “Rotate the model”, “Zoom in model”, “Banding zoom”, “Select a view” and “fit the model view on the window”
- 5 **Selecting an polymer injection location** The PA allows to work with single or multiple polymer injection locations
- 6 **Changing analysis results** : The PA allows you to change some of the model processing conditions. In the “material properties” area, we can change the mold temperature and the melt temperature from the defaults to custom values. In the maximum pressure injection limit area, we can change the maximum pressure injection limit from the default values to a custom value, and we can also change the default value. In the “machine injection time area” we can enter a particular time value. These changes are not compulsory steps for each analysis
- 7 **Save the model** Saving will ensure that all the conditions you have set so far will be saved. They include polymer selected, the rotation of the model, the injection location and the current maximum injection pressure limit
- 8 **Run the PA** In this step we run the PA to fill the model. The filling process will display dynamically on the 3d model and show the plastic flow. Filling the model will take approximately 5 - 10 minutes. During filling, the status bar at the base of the screen will

display the current progress bar to indicate progress. When filling has been completed the status bar will display *ready*

9 **Results :** Various results that can be viewed after the analysis

- Confidence of fill
- Fill Time
- Pressure Drop
- Flow front Temperature
- Weld lines
- Air traps
- Injection Pressure

### 5.2.3 Features of Part Adviser 3.0

- 1 After the analysis has finished, you can look at the confidence of fill result, which is derived from the filling time, injection pressure, pressure drop and temperature. The confidence result is displayed in three colours. A green area has a “high” confidence rating, yellow indicates a “medium” confidence rating, while red shows a ”low” confidence rating. There are number of confidence of fill advice help topics that give suggestions on how to improve a medium or low result. If the confidence of fill result does indicate problems, we can look at the filling time, injection pressure, pressure drop and temperature results to determine the reason for the low or medium confidence of fill. If the confidence of fill results shows any molding problem, we can identify the problem after looking at the pressure and the temperature results. We can find out the other problems after looking at the Weld lines and Air trap results.

- 2 PA provides advice on specific aspects of the filling process, provide explanations of potential problems allow you to make certain changes that may lead to solution for filling difficulties
- 3 For clarity of the users PA has clipping plane to view “hidden” sections of the model as well as an X-Y-Z rotation axes display
- 4 PA will provide with the enhanced web based reports after the analysis is completed

### 5.2.4 Simulation Results

In this section various results and some of the plots obtained by the PA is presented with the help of a trial run. As mentioned earlier PA generates a report after each simulation is completed, which contains the results summary and the various plots like temperature plot, pressure drop plot etc, to interpret the results. For this section we have taken the example “Diskcady” as the part and the various settings are made as explained in the section 5.2.2 and the simulation is done

Figure 5 7 is the injection pressure plot given by the PA after the process simulation. In this plot colour (which can not be viewed in this black and white picture) at each place on the model represents the pressure at the place on the model, at the moment of the part is filled completely. This is a “snapshot” result, that is it shows the pressure through the whole part at the end of fill. In this plot, range of colours are used to indicate the region of lower pressure (coloured blue) through to the region of highest pressure (coloured red). From this plot *maximum injection pressure ( $P_{max}$ )* is noted

Figure 5 8 shows the changes in the temperature of the flow front during filling. This result uses a range of colours to indicate the region of lowest temperature (coloured blue) through to

the region of highest temperature (coloured red). From this plot *temperature difference* is noted, by taking the difference between the maximum and minimum temperatures (indicated in the scale situated on the right side of the plot).

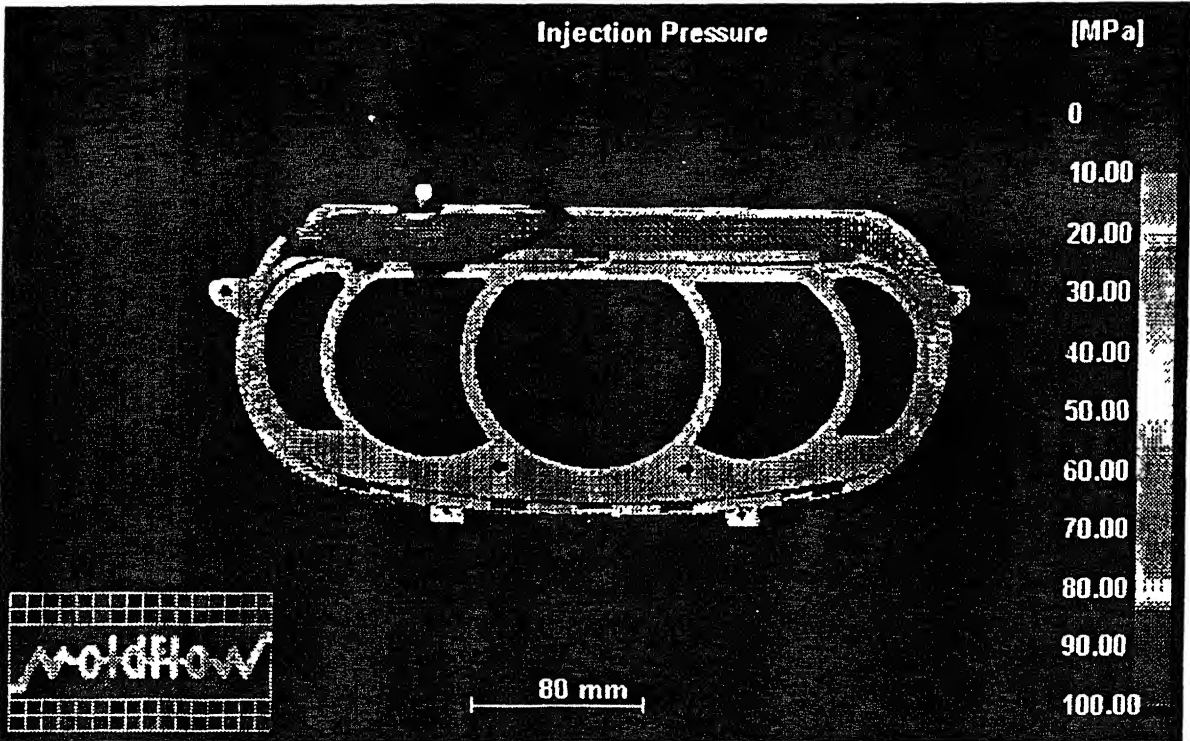


Figure 5.7 Injection pressure plot  
Flow Front Temp.

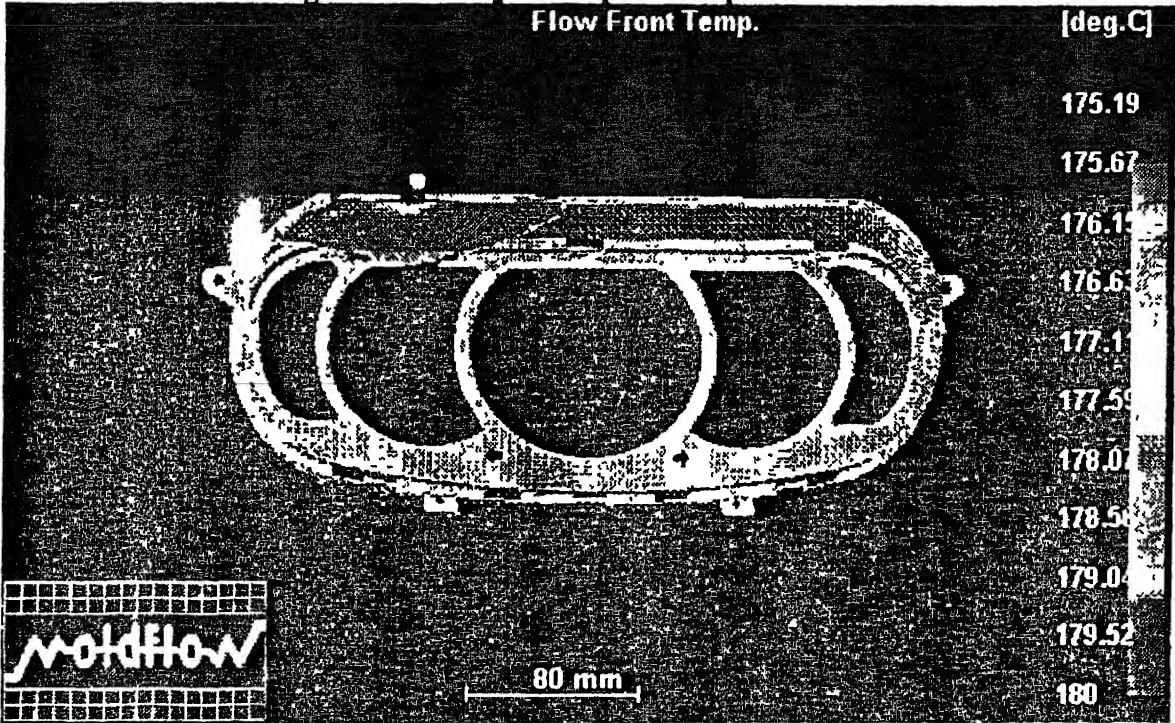


Figure 5.8 Flow front temperature plot

Figure 5.9 is the fill time plot. This plot shows the flow path of the plastic through the part. Each colour shown (which can not be viewed in this black and white picture) represents the parts of the mold which were being filled at the same time. A short shot (a part of the model which did not fill) will be displayed as translucent. In this plot range of colours used to indicate the first region to fill (coloured red) through to the last region to fill (coloured blue). The value of *actual fill time* is noted down from this plot.

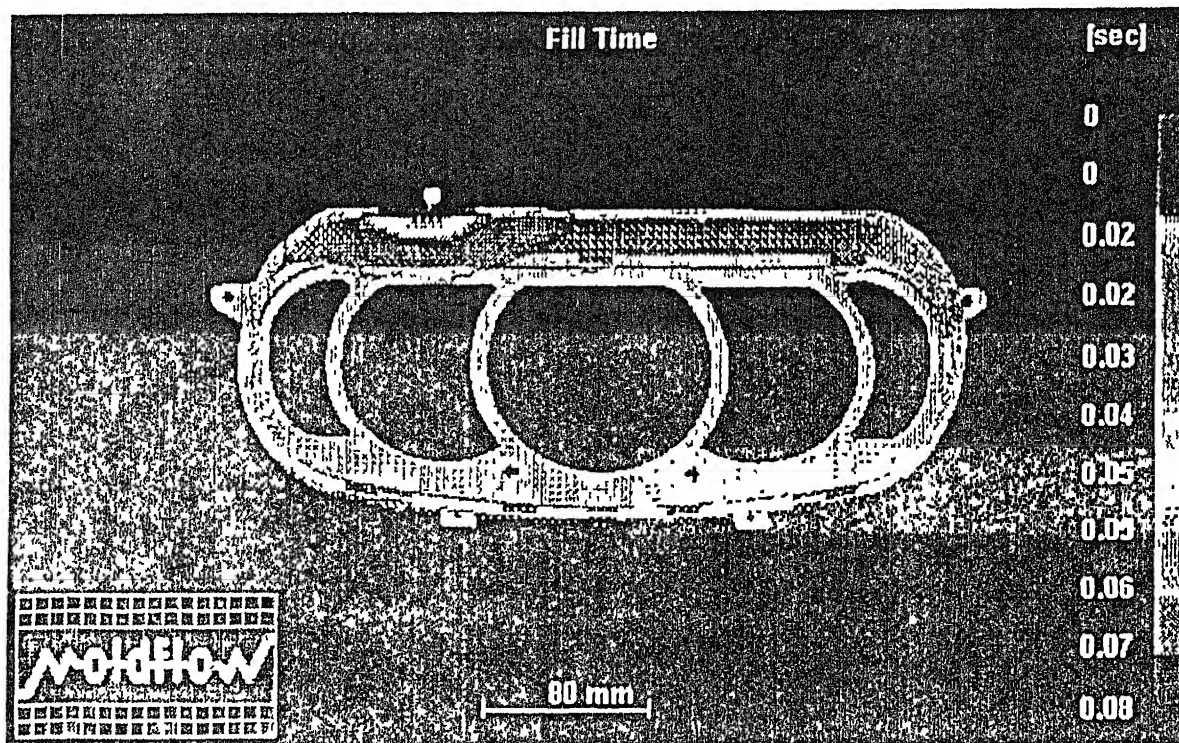


Figure 5.9 Fill time plot

## CHAPTER 6

# MULTIPLE REGRESSION

### 6.1 Introduction to Regression analysis

In any system in which variable quantities change, the interest might be in assessing the effects of the factors on the behaviour of some measurable quantity (the response). Such an assessment is possible through regression analysis. Regression analysis is a statistical technique for investigating and modeling the relationship between variables. Using data collected from a set of experimental trials, regression helps to establish empirically (by fitting some form of mathematical model) the type of relationship that is present between the response variable and its influencing factors. The response variable is the dependent variable and is called the *response*, and the levels of the influencing factors are called *predictor*, *regressor*, or *input* variables. Regression analysis is one of the most widely used tools for investigating cause-and-effect relationships having applications in the physical, biological, and social sciences, as well as in engineering and in many other fields (Montgomery and Peck, 1992).

By *predictor* or *independent* variables we shall usually mean variables that can either be set to be a desired value or else take value that can be observed but not controlled. Independent variables in a regression analysis can be qualitative as well as quantitative (Khuri and Cornell, 1987). The specific independent variables whose levels are to be studied in detail are those that are quantitative in nature, and their levels (or settings) are assumed to be controlled (without error) by the experimenter. As a result of changes that are deliberately made, or simply take place in the predictor variables, an effect is transmitted to other variables, the *response* variable.

The distinction between predictor and response variables is not always completely clear cut and depends sometimes on our objectives. What may be considered a response variable at a midstage of a process may also be regarded as predictor variable (Draper and Smith, 1981).

## 6.2 Multiple Regression analysis

A regression model that involves more than one regressor (independent) variable is called a multiple regression model. When there are more than one independent variables influencing the response variables, the method adopted to build the model is the multiple regression. Before one starts to build an empirical model, it is very necessary to understand the range (of variables) in which model has to be developed, because developed model may be linear in some part of the range and nonlinear in some other part of the range. However if range is very large there is less chance for the model to be linear. In real life situations it is very rare that one encounters a linear model, but at the same time, a second order model is usually good enough to capture a great deal of information. To build a second order model, at least a *three-level* experimental design or plan is needed. For a five-factor experiment,  $3^5$  experiments are needed for a *full-factorial three level* design (Jugal, 1997). Thus full factorial design will certainly leads to a very accurate model (Jugal, 1997), but at the same time it will often be costly to do a such a large number of experiments. So, it is always the desire of the experimenter to choose a design which was fewer number of experimental runs, while at the same time, a high quality of information is generated from such an experimental design. Fractional factorial designs are therefore used to carry out the model estimation experiments. This does reduce the number of experimental runs, while giving good deal of good information about the process (Box and Behenkin, 1960)

Various designs used for developing second order models are described in section 4.4.

### 6.3 Response Surface Methodology (RSM)

RSM is a collection of mathematical and statistical techniques that are useful for modelling and analysis in applications where a response of interest is influenced by several variables and the objective is to *optimise the response*. The general RSM approach was developed in the early 1950's, and from last twenty years RSM has found extensive applications in a wide variety of industrial settings, ranging from chemical processes, semiconductor and electronic manufacturing, machining, metal cutting, and joining processes, among many others (31).

RSM is a set of techniques that encompasses (Khuri and Cornell, 1987)

1. Setting up a series of experiments (designing a set of experiments) that will yield adequate and reliable measurements of the response of interest
2. Determining a mathematical model that best fits the data collected from the design chosen in (1), by conducting appropriate tests of hypotheses concerning the model's parameters and
3. Determining the optimal settings of the experimental factors that produce the maximum (or minimum) value of the response

If discovering the best value, or values, of the response is beyond the available resources of the experiment, then response surface methods are aimed at obtaining at least a better understanding of the overall system (Khuri and Cornell, 1987).

Box and Draper (1975) have listed 14 properties of a response surface design to be used when fitting a polynomial model to data collected at the design points. Some of the features of a desirable design are as follows (Montgomery, 1997). Such a design

- 1 Provides a reasonable distribution of sampling or data points ( and hence information) through out the region of interest
- 2 Allows the model adequacy, including lack of fit, to be investigated
3. Allows experiments to be performed in blocks
4. Allows designs of higher order to be built up sequentially.
5. Provides an internal estimate of error.
- 6 Does not require a large number of runs
- 7 Does not require too many levels of the independent variables
- 8 Ensures simplicity of calculation of the model parameters.

These features are sometimes conflicting, so judgement must often be applied in design selection

## 6.4 Designs for Fitting the Second-Order Model

A design by means of which observed values of the response are collected for estimating the parameters in the second-order model ( Eq 6 1) is called a *second-order design* (Khuri and Cornell, 1987)

$$Y = \beta_0 + \sum_{i=1}^k \beta_i X_i + \sum_{i=1}^k \beta_{ii} X_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^k \beta_{ij} X_i X_j + \varepsilon \quad (6.1)$$

where  $X_1, X_2, \dots, X_k$  are the input variables which influence the response  $Y$ ,  $\beta_0, \beta_i$  ( $i = 1, 2, \dots, k$ ),  $\beta_{ij}$  ( $i = 1, 2, \dots, k, j = 1, 2, \dots, k$ ) are unknown parameters, and  $\varepsilon$  is a random error (contribution of factors not included in (6 1))

Since model (6.1) contains pure quadratic terms, any second-order experimental design must involve at least three levels of each input variable. In the following sections various second-order designs are discussed.

### 6.4.1 The $3^k$ Factorial Design

One possible second-order design is the  $3^k$  factorial design, which requires that the response be observed at all possible combinations of the levels of  $k$  input variables which have three levels each. In this case of  $3^k$  factorial designs, the number  $N$  of experimental trials is  $N = 3^k$  and can thus be excessively large, especially when a large number of input variables are under study. To reduce the total number of experimental design points, the use of fractional replications of these designs can be considered (Khuri and Cornell, 1987).

DeBaun (1959) introduced a number of three-factor, three-level designs. These designs consist of a combination of the following subsets of points taken from the  $3^3$  design.

1. The  $3^3$  factorial design
2. Cube (points at  $(\pm 1, \pm 1, \pm 1)$ )
3. Center point  $(0, 0, 0)$ .
4. Octahedron (points at  $(\pm 1, 0, 0, \pm 1, 0, 0, \pm 1)$ )
5. Cuboctahedron (points at  $(\pm 1, \pm 1, 0, \pm 1, 0, \pm 1; 0, \pm 1, \pm 1)$ )

The designs investigated by DeBaun were:

1. The  $3^3$  factorial design
2. Cube + octahedron +  $n$  center points.
3. Cube + 2 octahedron +  $n$  center points.
4. Cuboctahedron +  $n$  center points

5. Cube + cubeoctahedron +  $n$  center points
6. Cuboctahedron + octahedron +  $n$  center points

DeBaun compared the above six designs on the basis of the value  $\{\text{Var}(\hat{Y}(x))/\sigma^2\}^{-1}/N$  at  $(0, 0, 0)$  in addition to its distribution on  $\rho = (x'x)^{1/2}$  along certain radii. He concluded that the  $3^3$  design is by no means the most efficient of the cases 1-6, he found that  $3^3$  design is, in particular, excelled by the *cube plus two octahedral design* with 22 and 24 points, respectively, and by the cuboctahedron design with 16 points.

#### 4.4.2 Box-Behenkin Designs

Factorial designs for the estimation of the parameters in a second-order model was developed by Box and Behenkin (1960). By definition, a three level incomplete factorial design is a subset of the factorial combinations from a  $3^k$  factorial design. The Box-Behenkin designs are formed by combining two-level factorial designs with balanced incomplete block designs in a particular manner. The interesting feature of these designs is these are “corner free”. No runs are done at the design corners. There are no experiments where at least one of the factors is not at its midpoint. In contrast, to the CCD designs (discussed in the next section), there are no axial points so each factor appears at only three (not five) levels.

#### 6.4.3 Central Composite Designs(CCD)

Box and Wilson (1951) introduced an alternative class of designs to the  $3^k$  factorial designs, namely, the class of central composite designs (CCD). CCD designs are considered to be most popular class of designs used for fitting the second-order models (Montgomery, 1997). A central composite design consists of

1. A complete (or fraction of a)  $2^k$  factorial design, where the factor levels are coded to the usual -1, +1 values. This is called the *factorial portion* of the design.
2.  $n_0$  center points ( $n_0 \geq 1$ )
3. Two axial points on the axis of each design variable at a distance of  $\alpha$  from the design center. This portion is called the axial portion of the design.

The total number of points is thus  $N = 2^k + 2k + n_0$ . There are two parameters in the design that must be specified, the distance  $\alpha$  of the axial runs from the design center, and the number of center points  $n_0$ .

A central composite design is made rotatable by the choice of  $\alpha$ . The value of  $\alpha$  for rotatability depends on the number of points in the factorial portion of the design; in fact,  $\alpha = (n_f)^{1/4}$  yields a rotatable central composite design where  $n_f$  is the number of points used in the factorial portion of the design. A choice of  $\alpha$  in the central composite design is dictated primarily by the region of interest. When the region of interest is sphere, the design must include center runs to provide reasonably stable variance of predicted response. Generally, three to five center runs are recommended.

## 6.5 Least square estimation of the regression coefficients

The method of least squares is typically used to estimate the regression coefficients in a multiple linear regression model. Least square estimates minimise the sum of squares of the deviation between the model and the data. The method tries to minimise the sum of squares of the residual. A model with  $n > k$  observations ( $k$  = number of independent variables  $\{x_i\}$ ,  $y_i$  denoting the  $i$ th observed response and  $x_{ij}$  denoting the  $i$ th observation or level of regressor  $x_j$  is as shown below

$$y_i = \beta_0 + \beta_1 \times x_{i1} + \beta_2 \times x_{i2} + \dots + \beta_k \times x_{ik} + \varepsilon_i$$

Here  $\varepsilon_i$  is the error. Assumptions made about the errors are (Khuri)

- 1 Random errors  $\varepsilon_i$  have zero mean and common variance,  $\sigma^2$ .
- 2 Random errors  $\varepsilon_i$  are mutually independent in the statistical sense
- 3 Random errors  $\varepsilon_i$  are normally distributed.

The method of least squares chooses the  $\beta$ 's in the equation so that the sum of the square of the errors,  $\varepsilon_i$ , is minimised. The above equation can be expressed in the matrix notation as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (6.5.1)$$

where

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1k} \\ 1 & x_{21} & \cdots & x_{2k} \\ \vdots & \vdots & & \vdots \\ 1 & x_{n1} & \cdots & x_{nk} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, \quad \text{and} \quad \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (6.5.2)$$

The sum of squares of the errors has to be minimised, because the some of the error terms might be positive and some might be negative. The task is to minimise the deviation from the actual data. The sum of squares of the residual can be written in the matrix form as

$$\sum_{i=1}^n \varepsilon_i^2 = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \quad (6.5.3)$$

The least squares estimate minimises the sum of squares of the residuals at the experimental points. Equation (6.3) is differentiated with respect to the  $\beta$ 's and equating all partial derivatives to zero, and solved for  $\beta$ 's, the least square estimates for the model is obtained.

When the input matrix is denoted in the format given below where the vector  $\beta$  is the estimate of the parameters and  $x$  is the input variable matrix and  $y$  is the response variable vector. Then least square estimates,

$$\hat{\beta} = (x^T x)^{-1} (x^T y) \quad (6.5.4)$$

The data  $\{x, y\}$  may be obtained from any of the statistical experimental schemes described earlier

## 6.6 Regression models

In this section various process models empirically built in the present study are presented. A total of four sets of second-order regression models are build. Three sets of models used the data generated from the MOLDFLOW PART ADVISER (PA) software and one model using the CMOLD 3D QUICK FILL software

### 6.6.1 Regression models from the simulation data of PA

As mentioned in Chapter 4 (section 4 4) operational considerations such as melt temperature and mold temperature and fill time affect part quality by changing the conditions under which the mold is filled PA software allows us to change these three important process condition settings So, these three parameters are taken as the regressor (*independent*) variables and maximum injection pressure, temperature difference and actual injection time is taken as a *responses*. We have taken two different three factor designs for building regression models for the above mentioned responses.

### 6.6.1.1 Central composite rotatable design for three factors

$$\begin{bmatrix} \pm 1 & \pm 1 & \pm 1 \\ \pm 1.682 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \pm 1.682 & \\ 0 & 0 & \pm 1.682 \end{bmatrix} * 6$$

**Central composite rotatable design for three factors (Cochran and Cox, 1957)**

The design shown above is the central composite rotatable design for three factors, five level experiment. This design is for estimating the parameters of the second order model. There are a total of twenty experiments, including six centre level experiments. Simulation experiments were carried out at all the twenty experimental runs. Responses “injection pressure”, “actual injection time” and “temperature difference” were observed. Each of the three responses was then separately used to develop the respective second-order models for injection pressure, actual injection time and temperature difference. Least square method is used to develop the various response models. These are shown below.

**Models developed for the part “diskcady” using Polystyrene as material**

$$\begin{aligned} \text{INJECTION PRESSURE} = & -189.01 + 0.573813 * X_1 + 2.501543 * X_2 - 17.356 * X_3 - \\ & 0.00649 * X_1^2 - 0.00695 * X_2^2 + 6.184467 * X_3^2 + 0.000177 * X_1 * X_2 \\ & - 0.09164 * X_1 * X_3 - 0.00212 * X_2 * X_3 \end{aligned} \quad (6.5.1)$$

$$\begin{aligned} \text{ACTUAL INJECTION TIME} = & 0.101043 - 0.00226 * X_1 - 0.00049 * X_2 + 1.06168 * X_3 - \\ & 8.2E-06 * X_1^2 - 3.5E-07 * X_2^2 - 0.00266 * X_3^2 + 1.41E-05 * X_1 * X_2 \\ & + 0.000189 * X_1 * X_3 + 7.31E08 * X_2 * X_3 \end{aligned} \quad (6.5.2)$$

$$\begin{aligned} \text{TEMPERATURE DIFFERENCE} = & 2.374117 + 0.03884 * X_1 - 0.02673 * X_2 + 0.852161 * \\ & X_3 - 3.4 \text{E-}05 * X_1^2 + 0.000123 * X_2^2 - 0.5303 * X_3^2 - 0.00027 * X_1 * \\ & X_2 - 0.01553 * X_1 * X_3 + 0.01963 * X_2 * X_3 \end{aligned} \quad (6.5.3)$$

where

$X_1$  = Mold temperature

$X_2$  = Melt temperature

$X_3$  = Injection time

Correlation diagrams for the above models relating actual values to the values obtained from the models are shown below

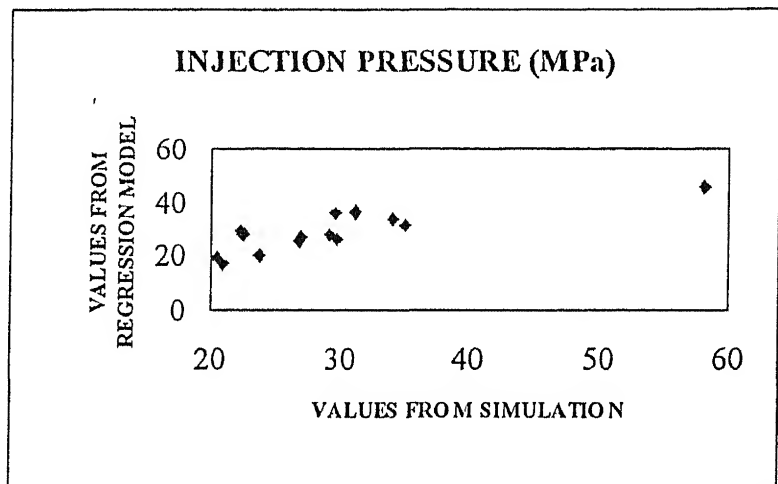


Figure 6.6.1

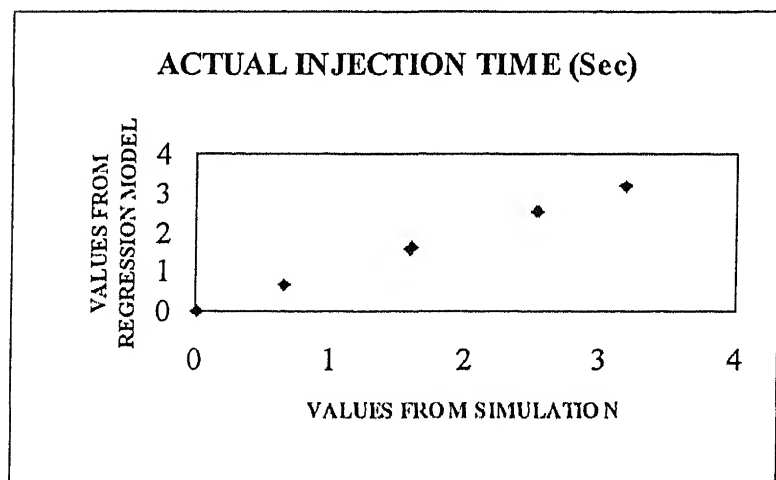


Figure 6.6.2

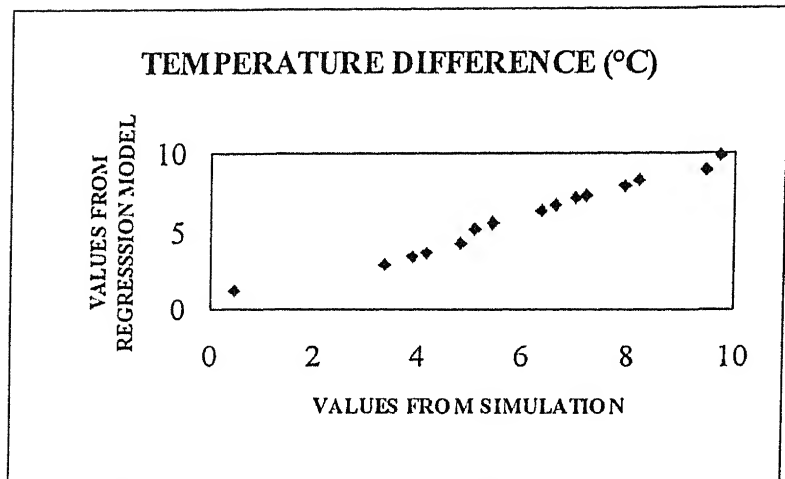


Figure 6.6.3

Correlation coefficients for the above models are shown in the table below

**Table 6.1** Correlation coefficients for the models developed using the design from the text book Cochran and Cox (1957).

Correlation Coefficients	
Injection pressure	0.825857
Actual injection time	0.999995
Temperature difference	0.989965

#### 6.6.1.2 $3^3$ factorial design

$\pm 1$	$\pm 1$	$\pm 1$
$\pm 1$	$\pm 1$	0
$\pm 1$	0	$\pm 1$
0	$\pm 1$	$\pm 1$
$\pm 1$	0	0
0	$\pm 1$	0
0	0	$\pm 1$
0	0	0

$3 \times 3 \times 3$  factorial design (Box and Draper, 1987)

The design shown above is the factorial design for a three factors, three level experiment. This design is for estimating the parameters of the second order model. There are a total of twenty seven experiments in this design. Simulation runs were carried out at all the twenty seven experimental settings using MOLD FLOW PART ADVISER software. The article “Diskcady” “Injection pressure”, “actual injection time” and “temperature difference” were observed as responses. Each of the three responses was then separately used to develop the respective multiple regression models for injection pressure, actual injection time and temperature difference. Least square method is used to develop these models for the above. This procedure is used to develop the second order model for the “diskcady” part using two different plastics, Polystyrene and LDPE. Models for both the materials are shown below.

**Models developed for the part “diskcady” using Polystyrene as material.**

$$\begin{aligned} \text{INJECTION PRESSURE} = & 288.139 - 0.15742 * X_1 - 1.45338 * X_2 - 66.66 * X_3 - 0.00065 \\ & * X_1^2 + 0.001644 * X_2^2 + 7.968747 * X_3^2 + 0.000945 * X_1 * X_2 - \\ & 0.04881 * X_1 * X_3 + 0.171098 * X_2 * X_3 \end{aligned} \quad (6.5.4)$$

$$\begin{aligned} \text{ACTUAL INJECTION TIME} = & 0.247042 - 0.00019 * X_1 - 0.00235 * X_2 + 1.06185 * X_3 - \\ & 1.8\text{E}-06 * X_1^2 + 5.56\text{E}-06 * X_2^2 - 0.0016 * X_3^2 + 1.67\text{E}-06 * X_1 * X_2 \\ & + 6.68\text{E}-05 * X_1 * X_3 + 2.22\text{E}-15 * X_2 * X_3 \end{aligned} \quad (6.5.5)$$

$$\begin{aligned} \text{TEMPERATURE DIFFERENCE} = & -5.87416 + 0.018823 * X_1 + 0.05786 * X_2 + 1.36318 * \\ & X_3 - 5.5\text{E}-05 * X_1^2 - 0.00013 * X_2^2 - 0.65733 * X_3^2 - 8.8\text{E}-05 * X_1 * \\ & X_2 - 0.01985 * X_1 * X_3 + 0.02146 * X_2 * X_3 \end{aligned} \quad (6.5.6)$$

where

$X_1$  = Mold temperature

$X_2$  = Melt temperature

$X_3$  = Injection time

Correlation diagrams for the above models relating actual values to the values obtained from the models are shown below

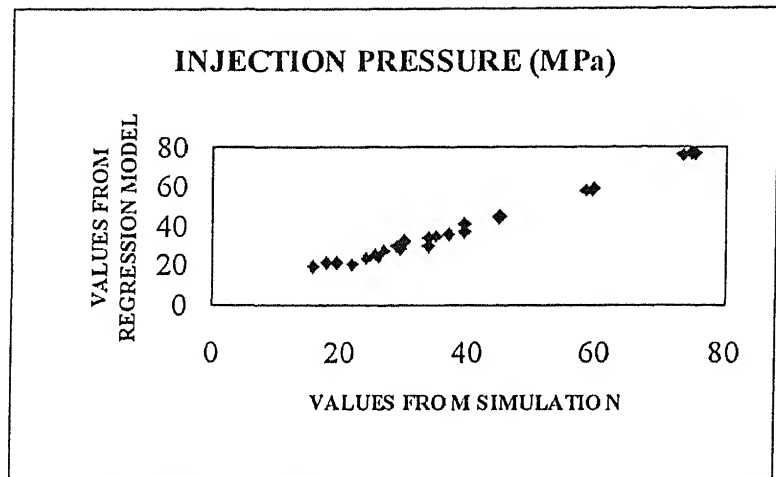


Figure 6.6.4

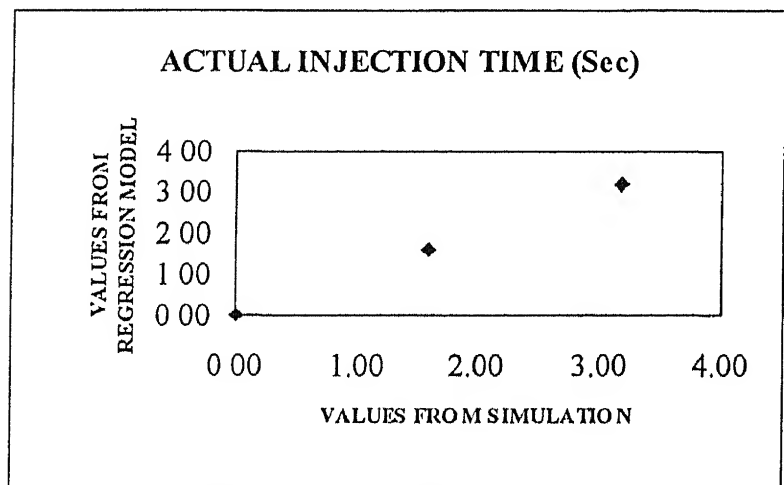


Figure 6.6.5

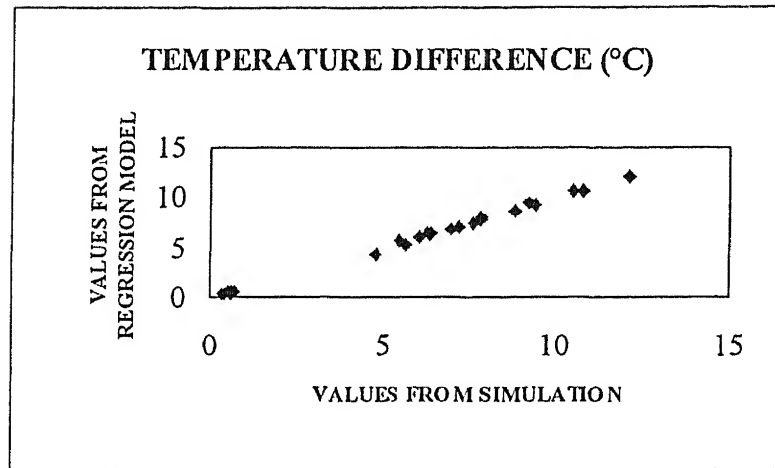


Figure 6.6.6

Correlation coefficients for the above models are shown in the table below.

**Table 6.2** Correlation coefficients for the models developed using the  $3^3$  design for “Diskcady” model using Polystyrene as material

Correlation Coefficients	
Injection pressure	0.994314
Actual injection time	0.999997
Temperature difference	0.999188

**Models developed for the part “diskcady” using LDPE as material:**

$$\begin{aligned}
 \text{INJECTION PRESSURE} = & 186.3289 - 0.14547 * X_1 - 0.551 * X_2 - 87.2293 * X_3 + \\
 & 0.000876 * X_1^2 + 0.000168 * X_2^2 + 12.0292 * X_3^2 + 0.000244 * X_1 * \\
 & X_2 - 0.02113 * X_1 * X_3 + 0.149972 * X_2 * X_3
 \end{aligned} \tag{6.5.7}$$

$$\begin{aligned}
 \text{ACTUAL INJECTION TIME} = & -0.21424 + 1.36E-05 * X_1 + 0.001889 * X_2 + 0.73517 * X_3 \\
 & - 1.0E-16 * X_1^2 - 4.2E-06 * X_2^2 + 0.000746 * X_3^2 - 3.3E-16 * X_1 * \\
 & X_2 + 2.79E-5 * X_1 * X_3 - 2.8E-05 * X_2 * X_3
 \end{aligned} \tag{6.5.8}$$

$$\begin{aligned}
 \text{TEMPERATURE DIFFERENCE} = & -4.75201 - 0.00028 * X_1 + 0.045121 * X_2 + 2.40199 * \\
 & X_3 - 4.0E-05 * X_1^2 - 9.0E-05 * X_2^2 - 0.79691 * X_3^2 - 1.7E-05 * X_1 * \\
 & X_2 - 0.02026 * X_1 * X_3 + 0.01847 * X_2 * X_3
 \end{aligned} \tag{6.5.9}$$

where \_

$X_1$  = Mold temperature

$X_2$  = Melt temperature

$X_3$  = Injection time

Correlation diagrams for the above models relating actual values to the values obtained from the models are shown below

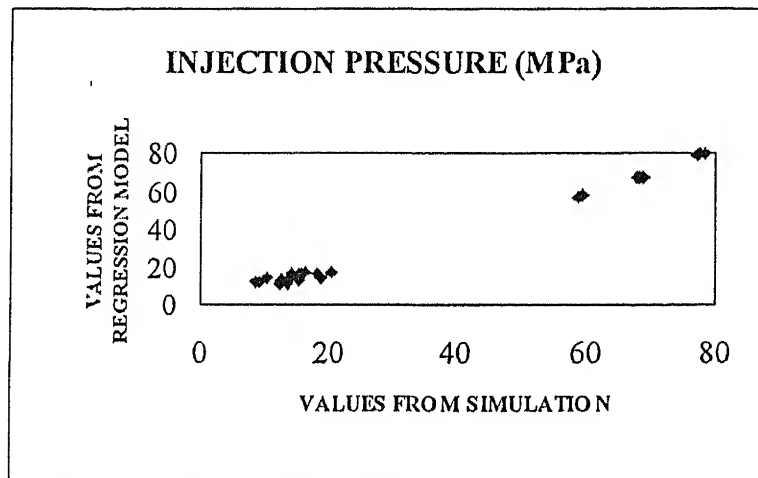


Figure 6.6.7

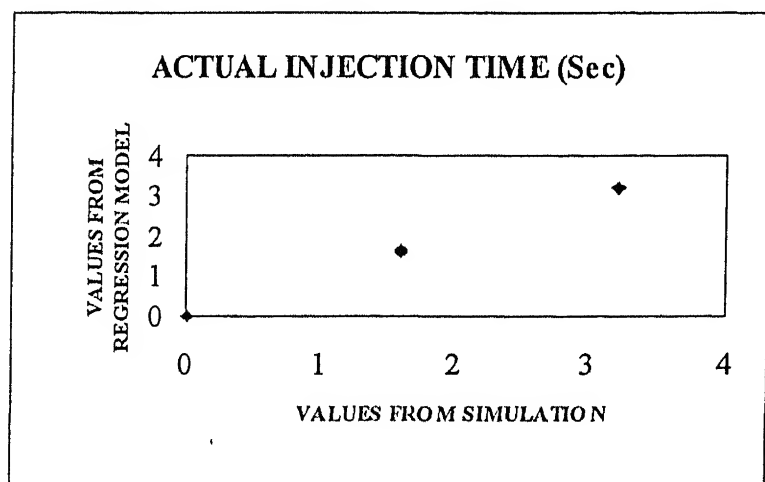


Figure 6.6.8

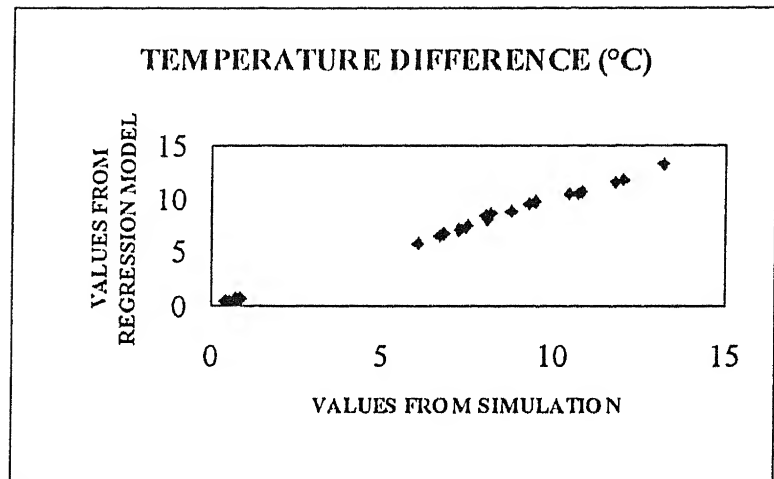


Figure 6.6.9

Correlation coefficients calculated for the above models are shown in the table below.

**Table 6.3** Correlation coefficients for the models developed using the  $3^3$  design for the “Diskcady” model using LDPE as material.

Correlation Coefficients	
Injection pressure	0.997018
Actual injection time	0.999997
Temperature difference	0.999137

### 6.6.2 Regression models from the simulation data of 3D Quick Fill

This software allows to change the process conditions melt and mold temperature and the molding machine parameters used for the process, the maximum injection pressure and the maximum injection rate. Though the machine parameters are not real process conditions, we have taken these parameters also as regressor (independent) variables as the 3D Quick Fill so showing change in the responses by changing these parameters Injection pressure, fill time, cooling time and temperature difference are taken as responses As there are four independent variables we have used Box and Behenkin four factor design for building the regression models

### 6.6.2.1 Box and Behenkin four factor design

±1	±1	0	0
0	0	±1	±1
0	±1	0	0
±1	0	±1	0
0	0	0	±1
0	0	0	0
0	±1	±1	0
±1	0	0	±1
0	0	±1	0
±1	0	0	0
0	±1	0	±1

**Box and Behenkin Design for Four Factors (Jugal, 1997)**

Shown above is the Box and Behenkin design for a four factor, three level experiment. Total thirty three runs are performed using CMOLD 3D QUICK FILL software for “tape” model. Parameters are estimated from the generated data for second order response model. Least square parameter estimate method is used to estimate the parameters. Responses for this experiments are “injection pressure”, “fill time”, “cooling time” and “temperature difference”. Regression models are developed for all four responses are listed below.

$$\begin{aligned} \text{INJECTION PRESSURE} = & 125.494 - 0.590052 * X_1 - 0.03866 * X_2 + 0.370962 * X_3 + \\ & 0.004097 * X_4 + 0.000786 * X_1^2 - 0.00017 * X_2^2 - 0.00037 * X_3^2 - 2.1\text{E-}07 \\ & * X_4^2 + 0.000206 * X_1 * X_2 - 0.00073 * X_1 * X_3 + 1.38\text{E-}06 * X_1 * X_4 - 7\text{E-} \\ & 05 * X_2 * X_3 - 6\text{E-}07 * X_2 * X_4 + 6.07\text{E-}06 * X_3 * X_4. \end{aligned} \quad (6.5.10)$$

$$\begin{aligned} \text{FILL TIME} = & 0.013339 - 2.1\text{E-}07 * X_1 - 2.5\text{E-}07 * X_2 - 2.4\text{E-}05 * X_3 - 1.3\text{E-}06 * X_4 + \\ & 1.99\text{E-}08 * X_1^2 - 8.9\text{E-}09 * X_2^2 + 2.34\text{E-}08 * X_3^2 + 5.56\text{E-}11 * X_4^2 + \\ & 1.87\text{E-}09 * X_1 * X_2 + 2.99\text{E-}08 * X_1 * X_3 + 2.81\text{E-}10 * X_1 * X_4 + 2.25\text{E-}09 \\ & * X_2 * X_3 + 2.25\text{E-}11 * X_2 * X_4 + 3.89\text{E-}10 * X_3 * X_4 \end{aligned} \quad (6.5.11)$$

$$\begin{aligned} \text{COOLING TIME} = & -0.10767 + 0.02642 * X_1 - 0.09467 * X_2 - 0.00023 * X_3 - 1.4\text{E-}05 * \\ & X_4 - 3.5\text{E-}05 * X_1^2 + 0.001353 * X_2^2 + 1.94\text{E-}07 * X_3^2 - 2.1\text{E-}10 * X_4^2 + \\ & 1.17\text{E-}05 * X_1 * X_2 - 9.4\text{E-}08 * X_1 * X_3 + 2.81\text{E-}08 * X_1 * X_4 - 1.88\text{E-}06 * \\ & X_2 * X_3 - 3.75\text{E-}08 * X_2 * X_4 + 7.5\text{E-}09 * X_3 * X_4 \end{aligned} \quad (6.5.12)$$

$$\begin{aligned} \text{TEMPERATURE DIFFERENCE} = & 8.899248 - 0.04484 * X_1 + 0.009147 * X_2 - 0.00991 * \\ & X_3 - 0.00034 * X_4 + 5.89\text{E-}06 * X_1^2 - 7\text{E-}05 * X_2^2 + 5.19\text{E-}06 * X_3^2 + \\ & 9.17\text{E-}09 * X_4^2 - 4.1\text{E-}15 * X_1 * X_1 + 2.81\text{E-}05 * X_1 * X_2 + 5.62\text{E-}07 * X_1 * \\ & X_4 - 4.3\text{E-}17 * X_2 * X_3 - 3.2\text{E-}13 * X_2 * X_4 - 1.3\text{E-}13 * X_3 * X_4. \end{aligned} \quad (6.5.13)$$

Where

$X_1$ . Melt temperature

$X_2$  Mold temperature

$X_3$ : Maximum injection pressure

$X_4$ . Maximum injection rate

Correlation diagrams for the above models relating actual values to the values obtained from the models are shown below

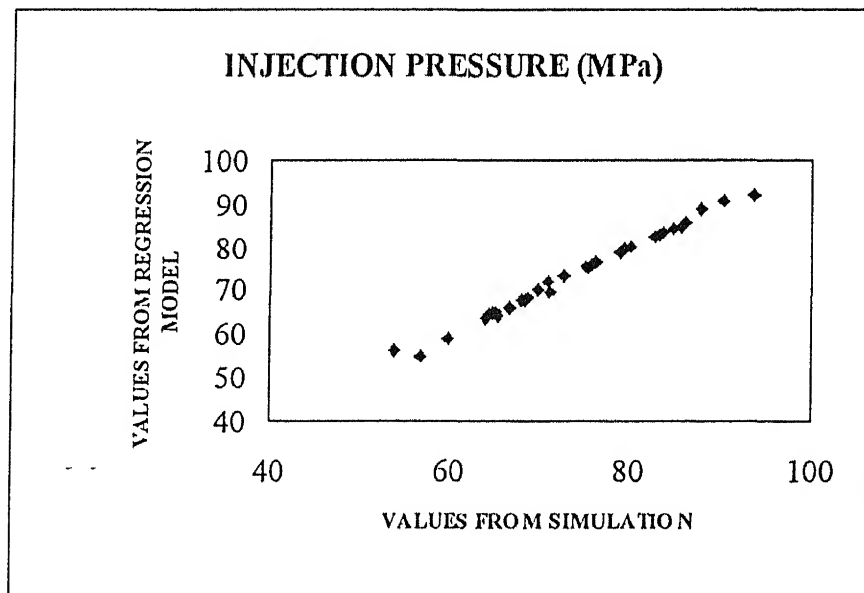


Figure 6.6.10

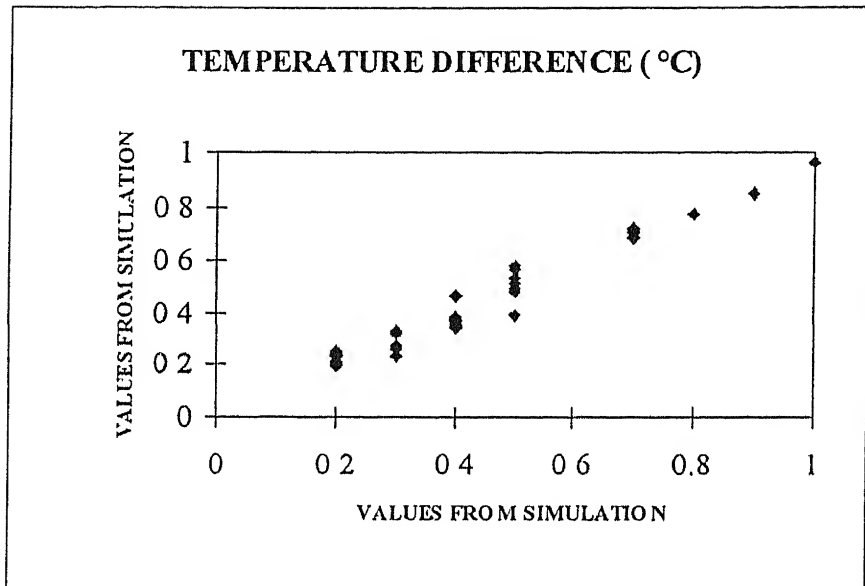


Figure 6.6.11

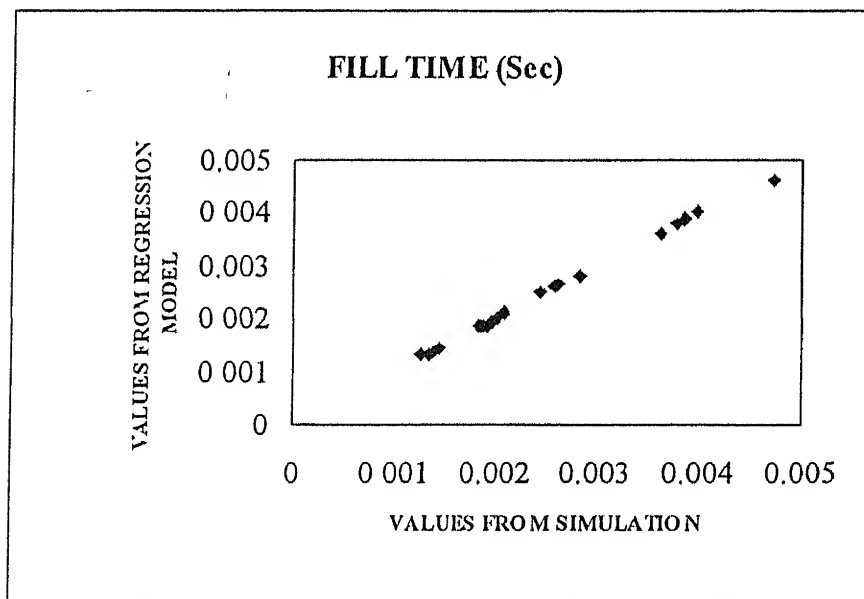
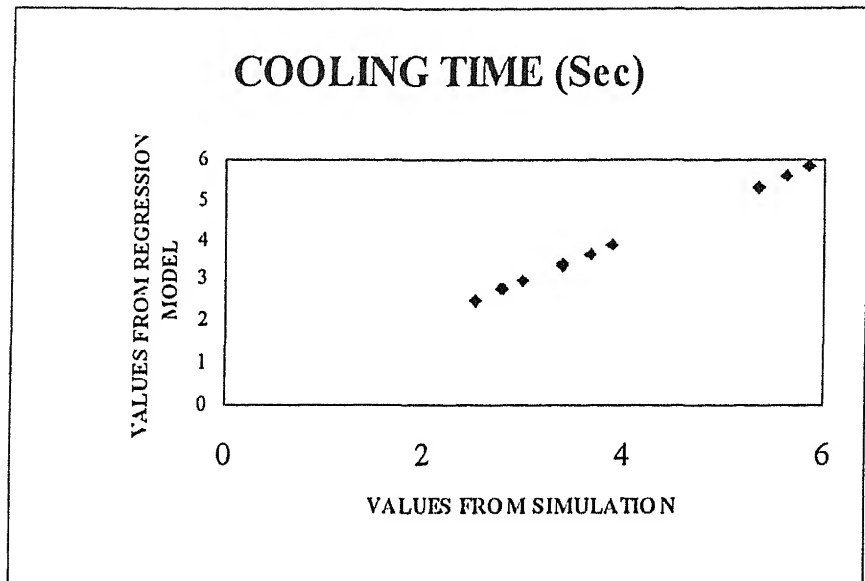


Figure 6.6.12



**Figure 6.6.13**

Correlation coefficients are calculated for the above models, which are shown in the table below

**Table 6.4** Correlation coefficients for the models developed using the Box and Behenkin design

Correlation Coefficients	
Injection pressure	0.997001
Fill time	0.999460
Cooling time	0.999995
Temperature difference	0.977995

## Summary

This chapter has developed the multiple regression process models that are subsequently used to optimise the responses by GA.

## Chapter 7

### RESULTS FROM SGA AND NSGA

In this chapter results obtained from the different single and multi-criteria optimisation problems attempted in this study are presented. The simple genetic algorithm (SGA) and non-dominated sorting genetic algorithm (NSGA), a new meta-heuristic are used for optimisation. Both SGA and NSGA are applied to four sets of empirically second-order regression models developed. Convergence graphs are shown from the results obtained from the execution of SGA. Pareto diagrams resulting from multi-criteria optimisation by NSGA are shown. Solution populations after fifty NSGA generations for several different multi-criteria optimisation attempted are shown in tables

As mentioned in the Section 5.2.2, the Moldflow simulator Part Adviser allows one to change three process conditions, namely, “melt temperature”, “mold temperature” and “injection time”. So, we used these three variables as *process variables* for building the regression models. From the various results that are given by Part adviser (listed in Section 5.2.2) we took “injection pressure”, “temperature difference” (noted from flow front temperature result) and “actual injection time” as *responses*.

The CMOLD simulator 3d Quickfill allows one to specify the process conditions “mold temperature” and “melt temperature”. It also allows one to specify three other molding machine parameters for the process, namely, the maximum injection pressure, the maximum injection rate and the machine performance. So, we used mold temperature, melt temperature, maximum injection rate and maximum injection pressure as *process variables* for developing regression

models For the various results that 3d Quickfill (listed in the Section 5.1.2) given we took “injection pressure”, “fill time” , “cooling time” and “temperature difference” as *responses*.

## **7.1 Evaluation of Factor effects of Moldflow Simulator responses**

To get the insight into which factors are important in a particular process one has to do the screening (David and Robert, 1998) One would accomplish this is by running a given factor at two levels (a high level and a low level) within a DOE framework and seeing if varying the level of this factor had any effect on the response. The simplest experimental design for accomplishing this is the Two level full factorial design So, to get the insight into responses of the Moldflow simulator, experiments were run using a  $2^3$  full factorial design The effect of varying the three process variables of Moldflow simulator on the three responses are shown in the Figures 7.1 to 7.3

Engineering considerations tell that increasing the melt and mold temperatures will reduce the required injection pressure, which we can see in Figure 7.1. As the melt and mold temperatures increase, the melt viscosity decreases hence there will be decrease in the injection pressure However, in the relationship between injection time and injection pressure, several contradictory factors come into play The shorter the injection time the higher is the volumetric flow rate, and the higher the pressure requirement. However, high speed injection also generates frictional (viscous heating) that raises the material temperature. The combined effect of high temperature and high shear rate (resulting from high flow rate) reduces the melt viscosity, and therefore offsets the pressure requirement. In the experiments see from the Figure 7.1 that with increase in injection time there is slight increase in injection pressure.

Figure 7.2 Factor effects on Temperature difference, Moldflow Simulator, 2<sup>3</sup> DOE

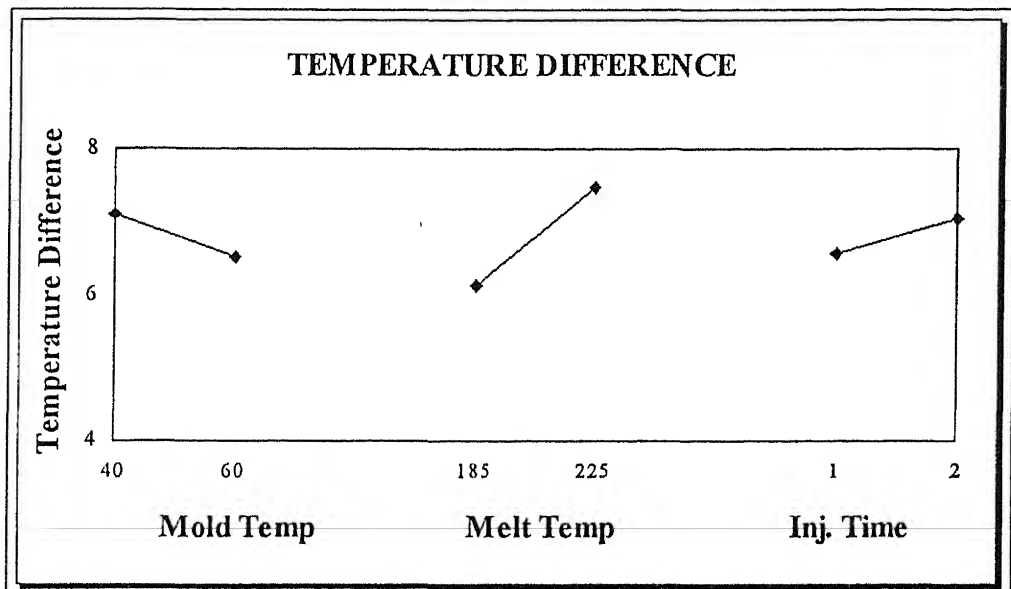
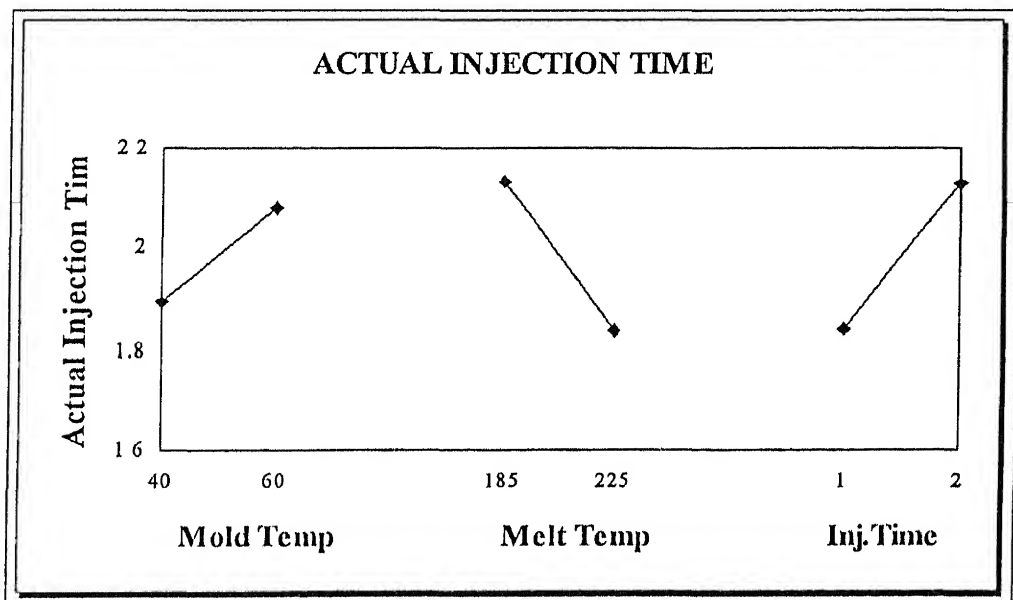


Figure 7.3 Factor effects on Actual injection time, Moldflow Simulator, 2<sup>3</sup> DOE



## 7.2 Results from Executing the SGA

When we use the SGA, we are interested in optimising a single objectives and in finding the single best solution GA responses chosen are usually the *best*, *average*, and the *worst* value of the objective function found after executing a fixed number of GA iterations Second-order regression models developed for each of the responses may be separately plugged in SGA for response evaluation These included the “injection pressure” , “actual injection time” and “temperature difference” regression models built using the simulation runs of Moldflow simulator “Injection pressure”, “fill time”, “cooling time” and “temperature difference” regression models built using the simulation runs of CMOLD simulator were used for the CMOLD processes

A fundamental result in genetic algorithms, the schema theorem (Goldberg, 1989), by itself is insufficient to guide the effective use of GAs in global optimisation It *does not* indicate what specific values should one choose for the different GA parameters, namely Population size,  $P_c$  and  $P_m$  etc , and the different schemes that introduced controlled amount of randomness while the GA is executing(Jugal, 1997) However, it is well known now that the GA's efficiency depends on high degree upon the selection of these “control parameters’ (Davis, 1991) A further complication exists because it is also widely reported that “optimum parameter settings” may be problem-specific, and that the effects of these parameters may interact Indeed, Davis notes that crossover and mutation effects can interact and “support each other in important ways” (Davis, 1991) Davis observes that a judicious blend of mutation and crossover does better than either one alone to strike a good balance between exploration of the total solution space and exploitation of good solutions currently at hand As it is noted above, the successful implementation of GA would depend upon the correctness in the choice of different parameters

that control its execution. A two level design of experiments is conducted to find the best combination of  $P_c$  and  $P_m$  keeping the other GA parameters constant. We found that the combination of 0.9 crossover probability and 0.005 mutation probability is giving the best results for hundred population. So following combination of GA parameters are used for SGA application:

Population size	=	100
Probability of crossover	=	0.9
Probability of mutation	=	0.005

Table 7.2.1 to Table 7.2.6 shows the best, average and worst values of responses after 50 generations of a four different experiment runs for Process models developed using  $3^3$  design on moldflow simulator. Table 7.2.1 to Table 7.2.3 shows the results for the second-order regression models for polystyrene diskcady and Table 7.2.4 to Table 7.2.6 is for LDPE diskcady.

Table 7.2.7 to Table 7.2.9 shows the best, average and worst values of responses after 50 generations for Process models developed using the CCD rotatable design on moldflow simulator for polystyrene diskcady.

Table 7.2.10 to Table 7.2.13 shows the best, average and worst values of responses after 50 generations for Process models developed using the Box and Behenkin design on CMOLD simulator for polypropylene tape casing.

Figure 7.2.1 to Figure 7.2.26 shows the convergence graphs for best and average values for the various second-order regression models developed after 50 generations.

**Table 7.2.1 : Injection pressure (MPa) values after 50 Generations for process model by 3<sup>3</sup> DOE on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	13.8284	15 6030	70.3796
30	13 7858	14 8402	74 2196
50	14 0934	15 5381	70 3709
75	13 9178	16 4729	67 6516

**Table 7.2.2 : Actual injection time (Sec) values after 50 Generations for process model by 3<sup>3</sup> DOE on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	0 0102	0 0562	3 1208
30	0.0128	0 0708	3.0334
50	0 0088	0 0489	3 0326
75	0 0128	0 0509	3 0681

**Table 7.2.3 : Temperature difference (°C) values after 50 Generations for process by 3<sup>3</sup> DOE on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	0 2826	0 3542	10 224
30	0 2826	0 3875	10 224
50	0.2901	0.4042	10 224
75	0 2826	0 4056	10 224

**Table 7.2.4 : Injection pressure (MPa) values after 50 Generations for process model by 3<sup>3</sup> DOE on Moldflow Simulator for LDPE Diskcady**

Seed	Best	Average	Worst
1	3 7623	4 2558	69 5169
30	3.7133	4.0710	69 5169
50	3 7529	4.2812	69 5169
75	3 7281	4 3255	69 5169

**Table 7.2.5 : Actual injection time (Sec) values after 50 Generations for process model by 3<sup>3</sup> DOE on Moldflow Simulator for LDPE Diskcady**

Seed	Best	Average	Worst
1	0 01	0 079	3.1462
30	0 01	0 0772	3.0619
50	0 01	0 0588	3.0585
75	0 01	0.0673	3.0924

**Table 7.2.6 : Temperature difference (°C) values after 50 Generations for process by 3<sup>3</sup> DOE on Moldflow Simulator for polystyrene Diskcady**

Seed	Best	Average	Worst
1	0 361	0.4482	11.568
30	0.361	0.4501	11.568
50	0 361	0 4511	11 568
75	0 361	0 4193	11.568

**Table 7.2.7 : Injection pressure values (MPa) after 50 Generations for process model by CCD rotatable design on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	9 6293	11 091	46 8810
30	9 4514	10.4182	49.334
50	9 4167	10 3166	45 7444
75	9 6317	11.7011	46.9483

**Table 7.2.8 : Actual injection time (Sec) values after 50 Generations for process model by CCD rotatable design on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	0 0075	0 0519	3 1258
30	0 0075	0 431	3.0314
50	0 0075	0 532	3.0314
75	0 0075	0.0433	3.0586

**Table 7.2.9 : Temperature difference (°C) values after 50 Generations for process model by CCD rotatable design on Moldflow Simulator for Polystyrene Diskcady**

Seed	Best	Average	Worst
1	0 7446	0 8734	10 2395
30	0 7446	0.7974	10.8202
50	0 7466	0 8513	10.2068
75	0 7446	0 8329	10 2068

**Table 7.2.10 : Injection pressure values (MPa) after 50 Generations for process model by Box and Behenkin design on CMOLD Simulator for Polypropylene Tape casing**

Seed	Best	Average	Worst
1	33 2792	37 1807	105 9656
30	32 8074	36 7974	105 9656
50	32 665	36 4936	105 9656
75	32 4539	36 6764	105 9656

**Table 7.2.11 : Fill time values (Sec) after 50 Generations for process model by Box and Behenkin design on CMOLD Simulator for Polypropylene Tape casing**

Seed	Best	Average	Worst
1	0 0010	0 0024	0 0085
30	0 0010	0 0035	0 0085
50	0.0010	0 0035	0.0085
75	0 0010	0 0026	0 0085

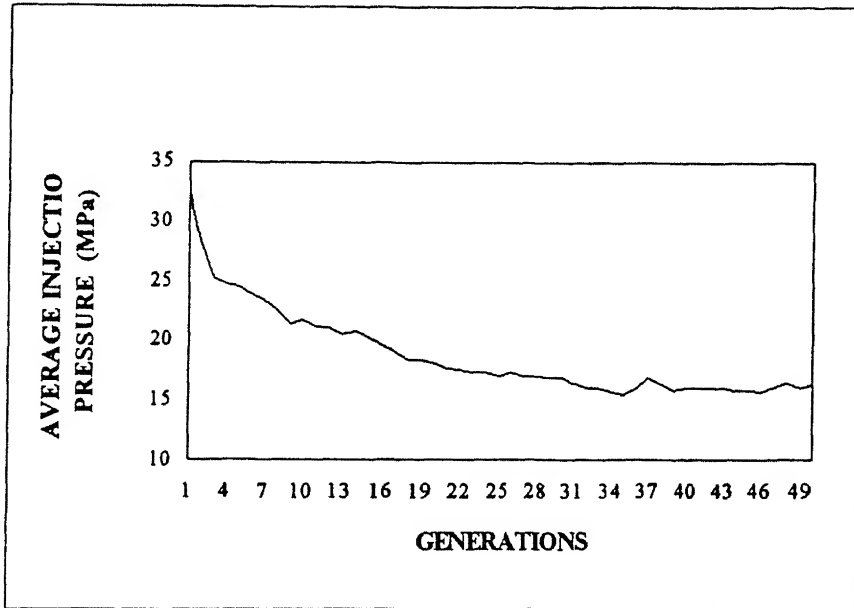
**Table 7.2.12 : Cooling time values (Sec) after 50 Generations for process model by Box and Behenkin design on CMOLD Simulator for Polypropylene Tape casing**

Seed	Best	Average	Worst
1	2.1566	2 2819	5 7449
30	2.1560	2 3523	5 7449
50	2 1539	2 4354	5 8153
75	2 1570	2 3984	5 7449

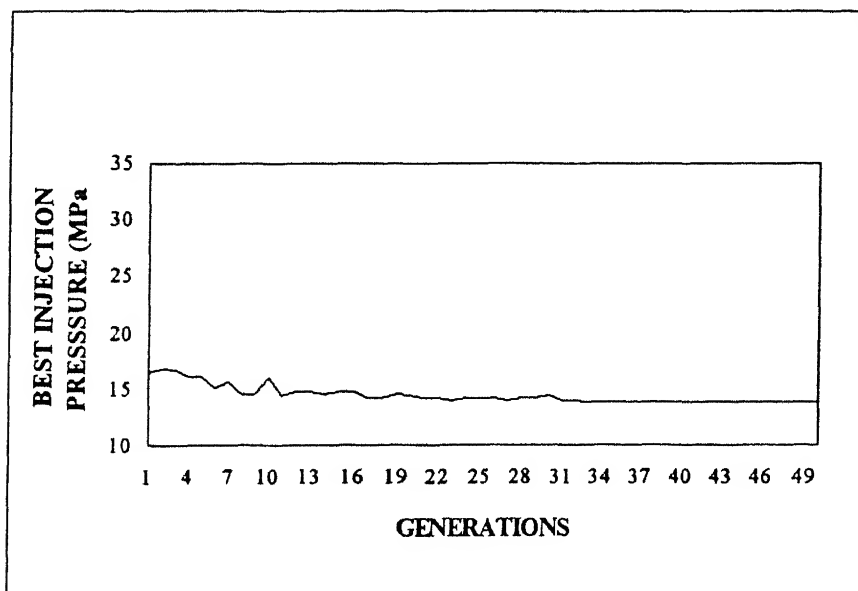
**Table 7.2.13: Temperature difference (°C) values after 50 Generations for process model by Box and Behenkin design on CMOLD Simulator for Polypropylene Tape casing**

Seed	Best	Average	Worst
1	0 1527	0 2081	2 0417
30	0 1490	0 2081	1.9269
50	0.1561	0 2284	1 9269
75	0 1506	0 1933	1 9629

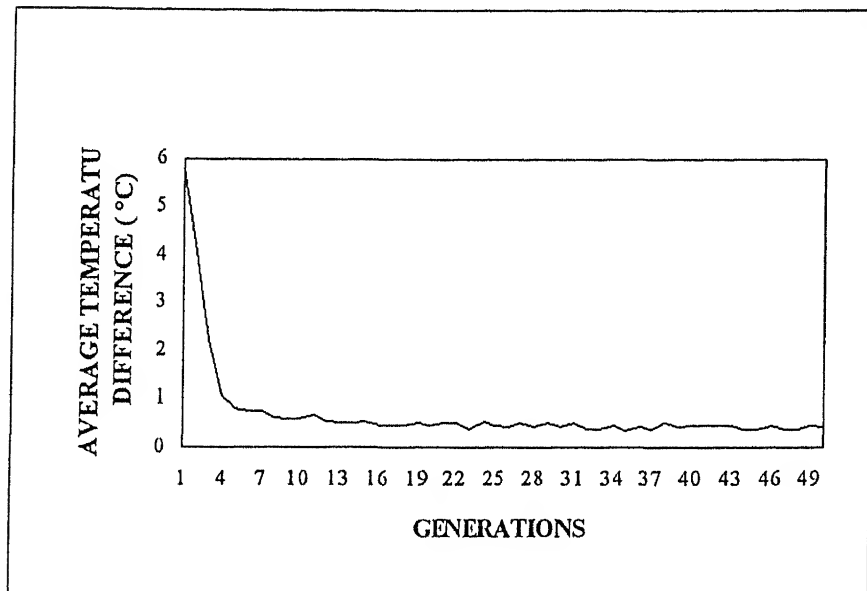
**Figure 7.2.1 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**



**Figure 7.2.2 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**



**Figure 7.2.3 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**



**Figure 7.2.4 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**

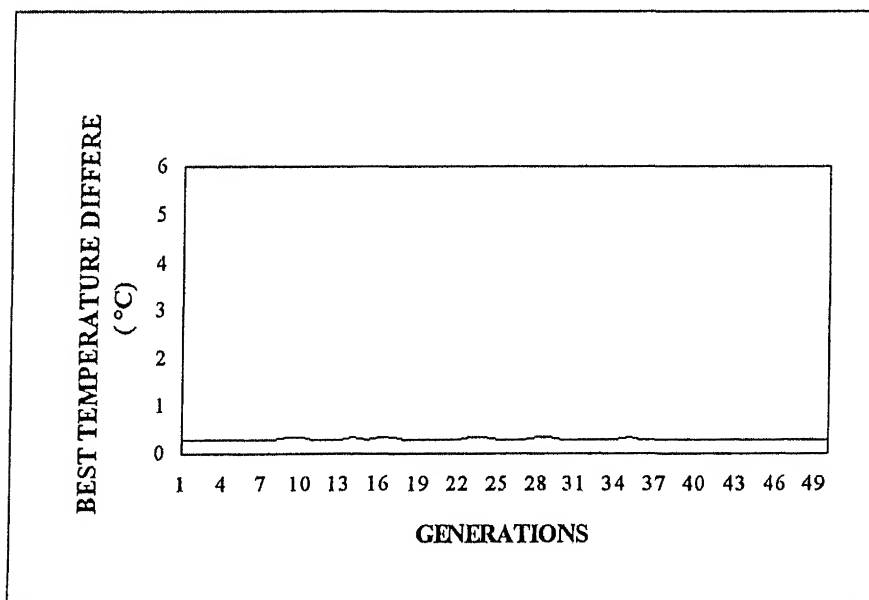


Figure 7.2.5 Convergence graph  
3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady

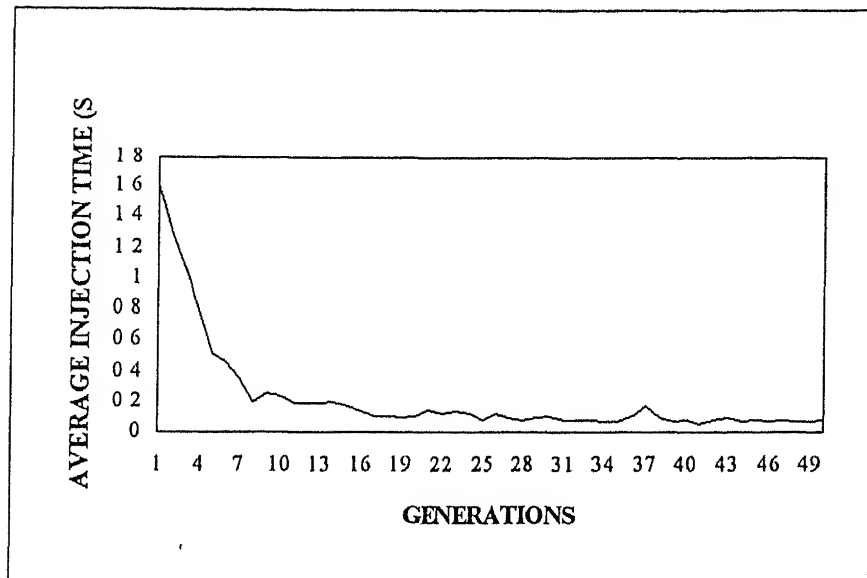
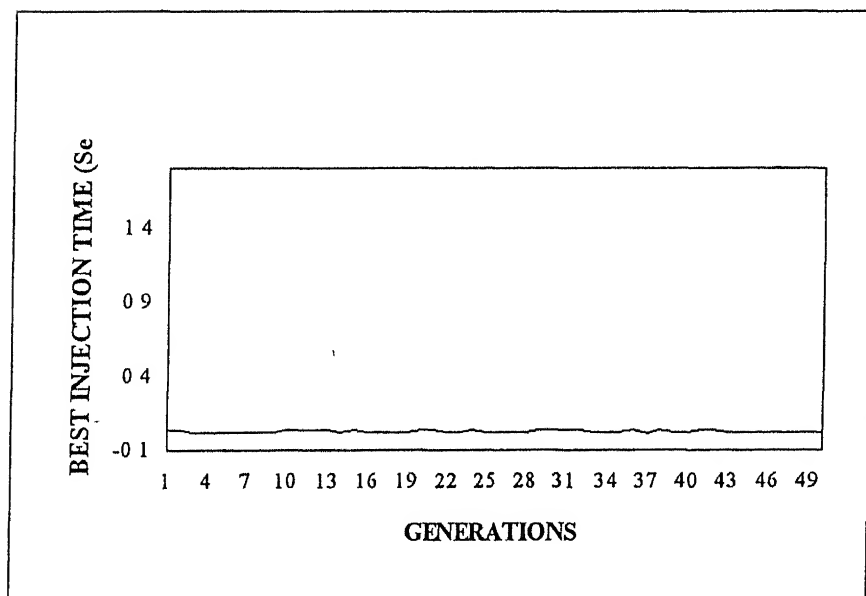
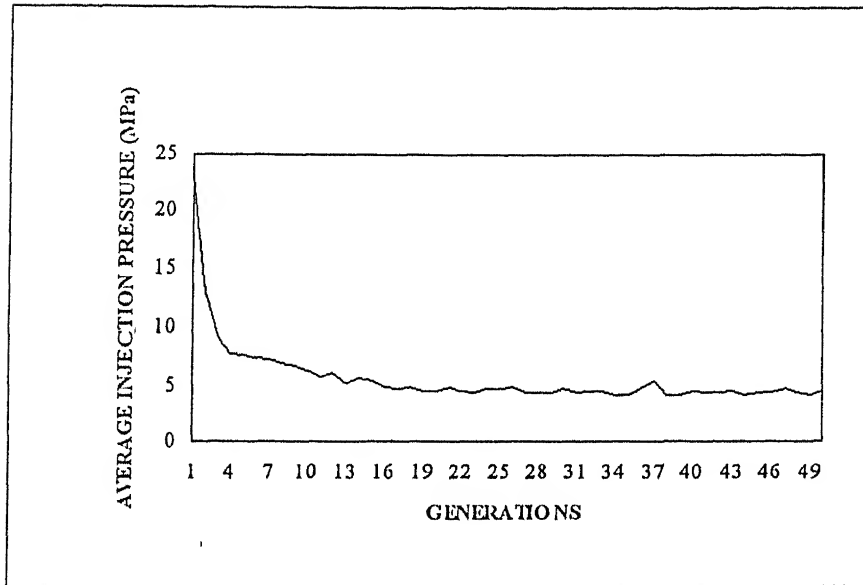


Figure 7.2.6 Convergence graph  
3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady



**Figure 7.2.7 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



**Figure 7.2.8 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**

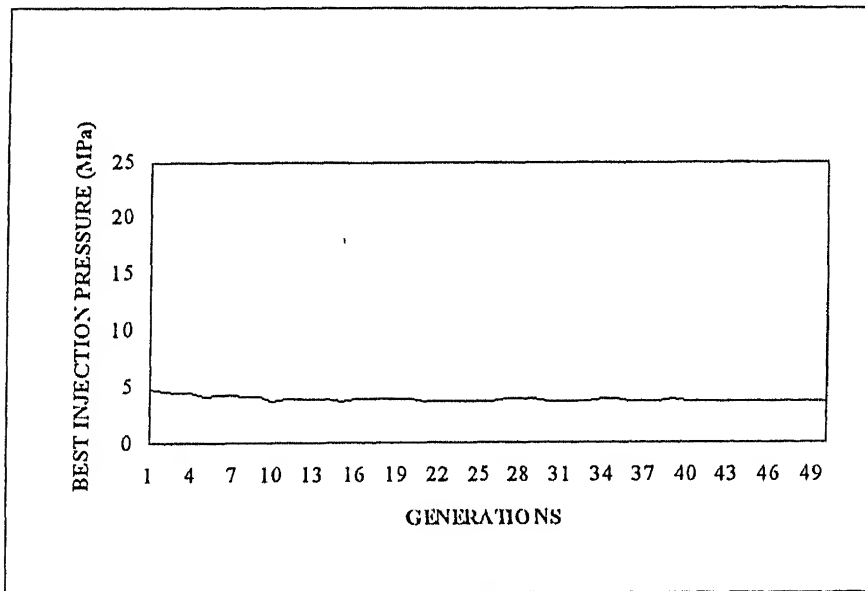


Figure 7.2.9 Convergence graph  
3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady

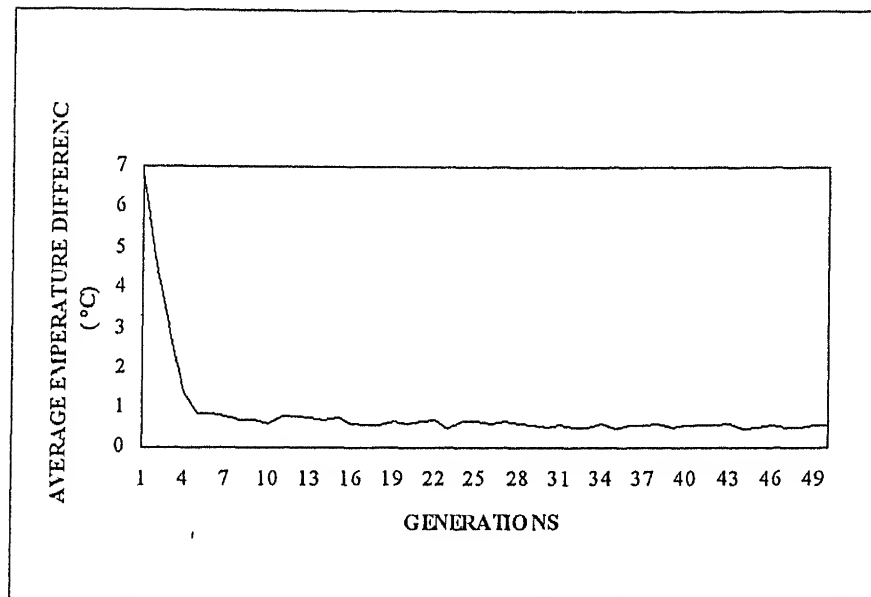
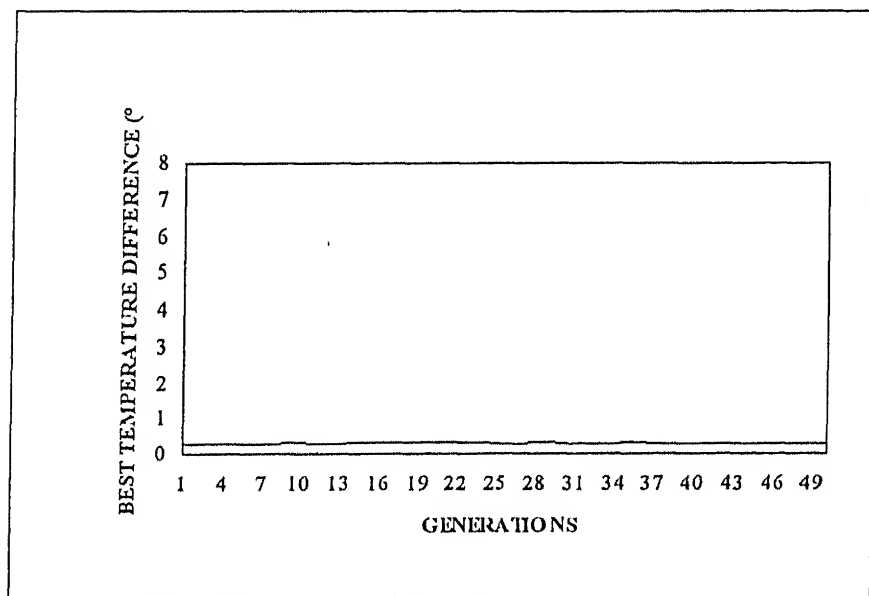
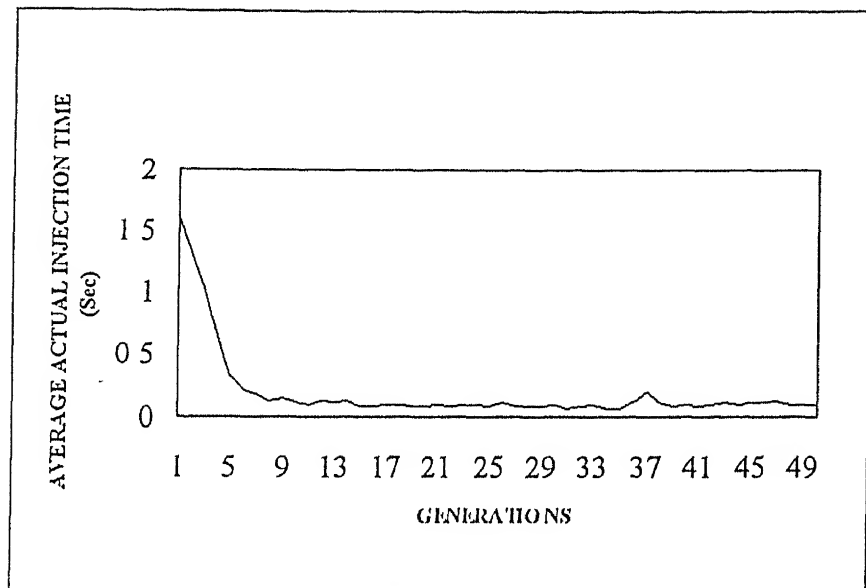


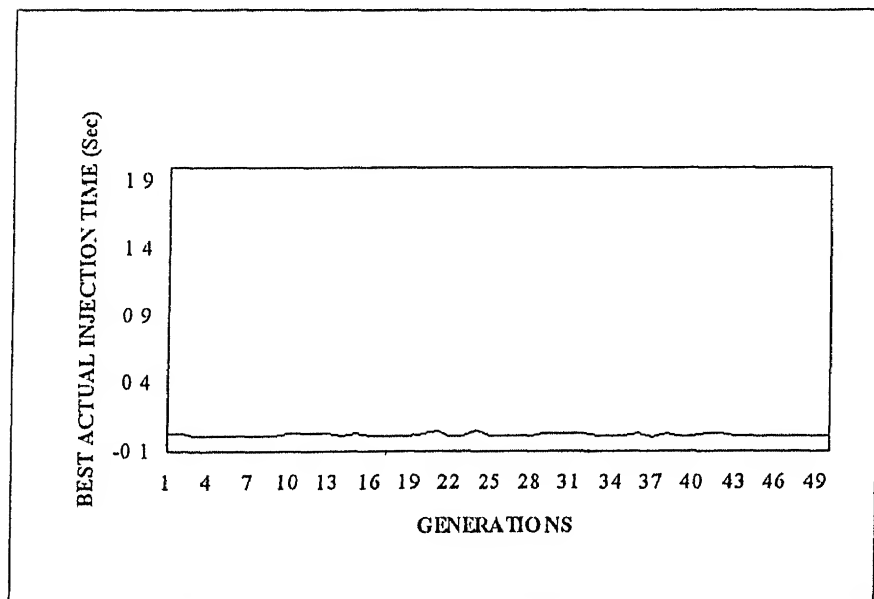
Figure 7.2.10 Convergence graph  
3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady



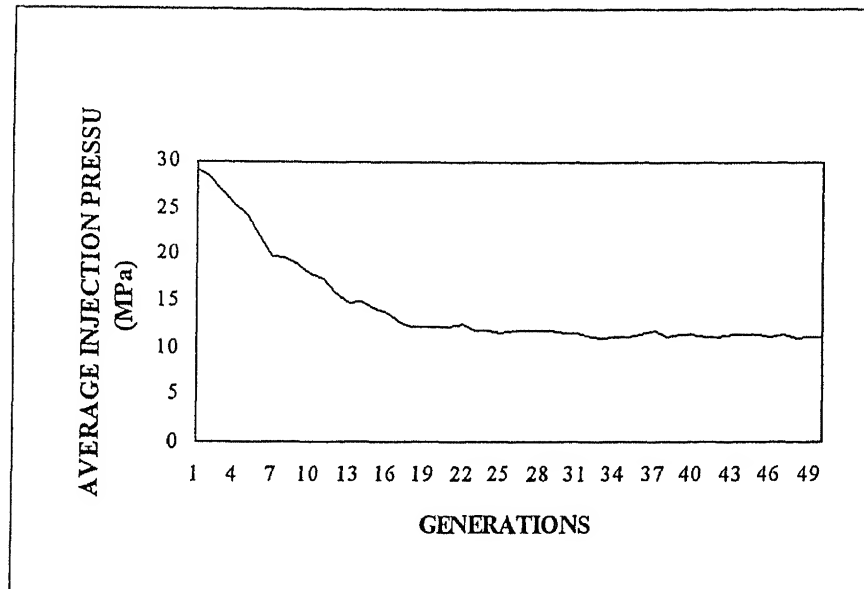
**Figure 7.2.11 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



**Figure 7.2.12 Convergence graph**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



**Figure 7.2.13 Convergence graph**  
**CCD model, Moldflow Simulator, Polystyrene Diskcady**



**Figure 7.2.14 Convergence graph**  
**CCD model, Moldflow Simulator, Polystyrene Diskcady**

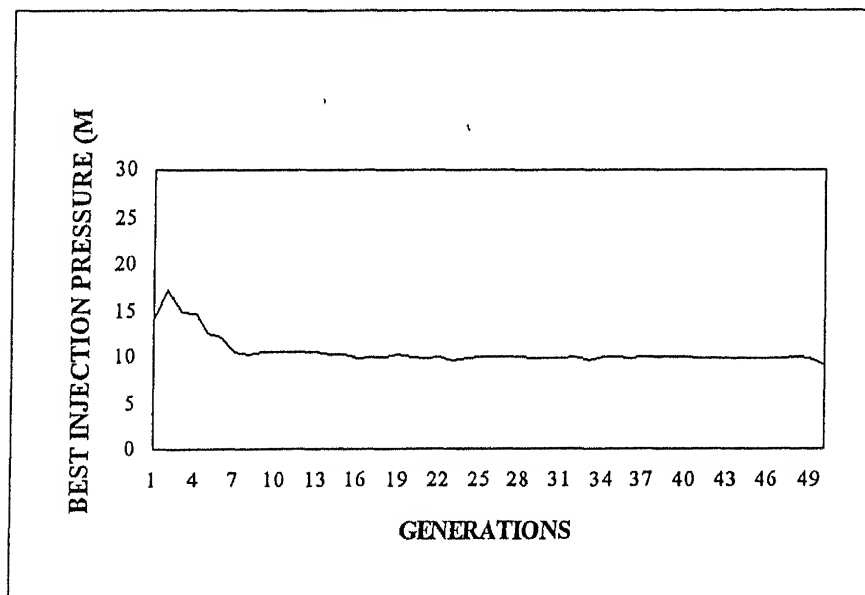


Figure 7.2.15 Convergence graph  
CCD model, Moldflow Simulator, Polystyrene Diskcady

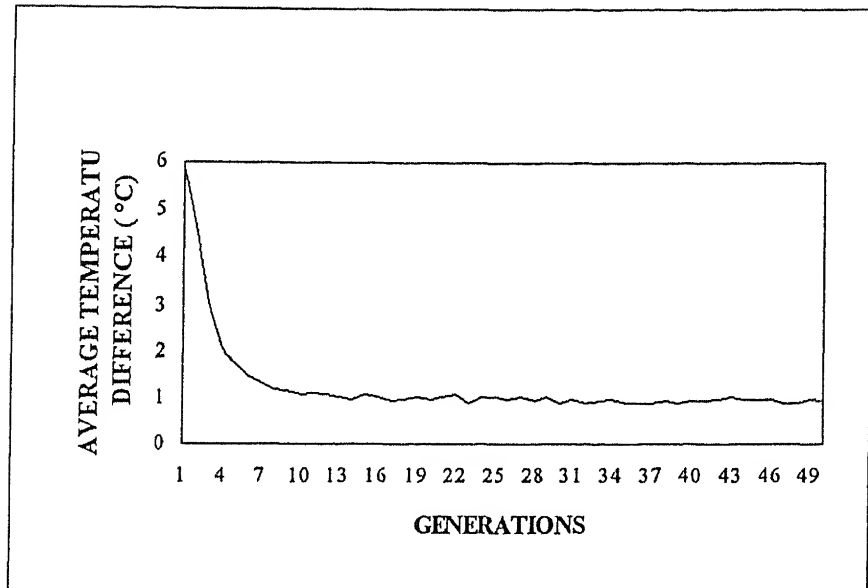


Figure 7.2.16 Convergence graph  
CCD model, Moldflow Simulator, Polystyrene Diskcady

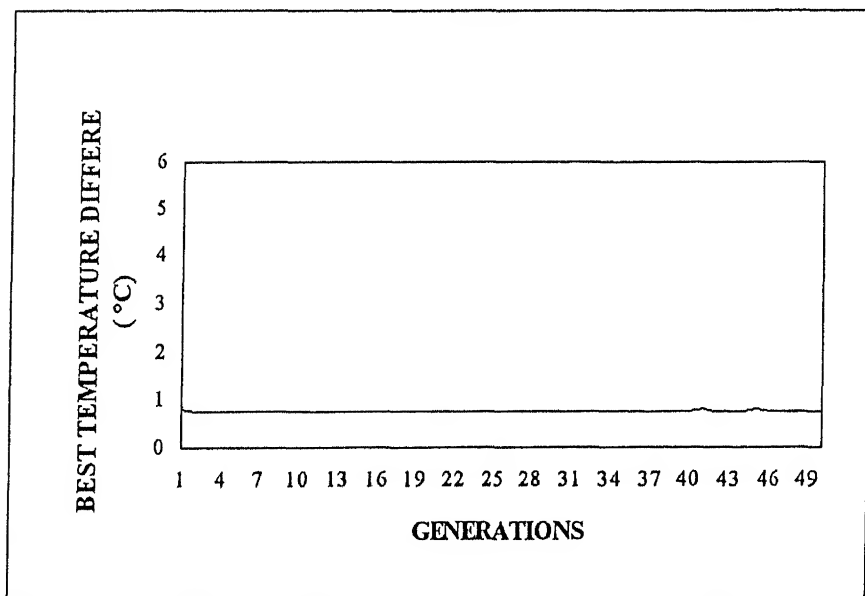


Figure 7.2.17 Convergence graph  
CCD model, Moldflow Simulator, Polystyrene Diskcady

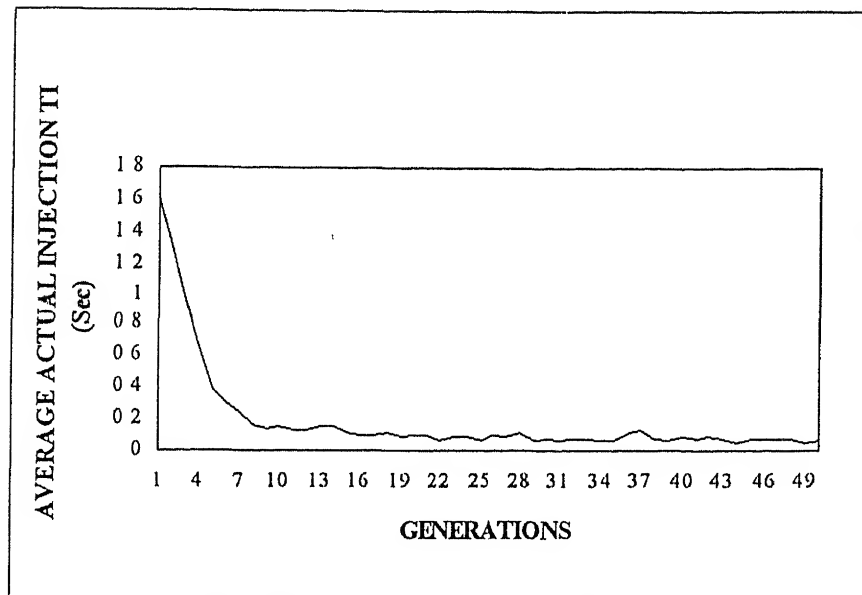
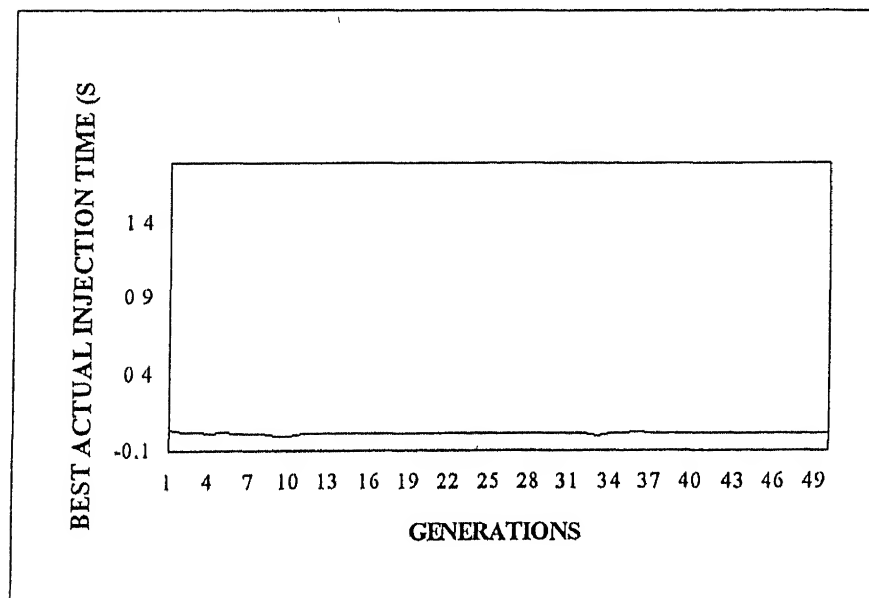
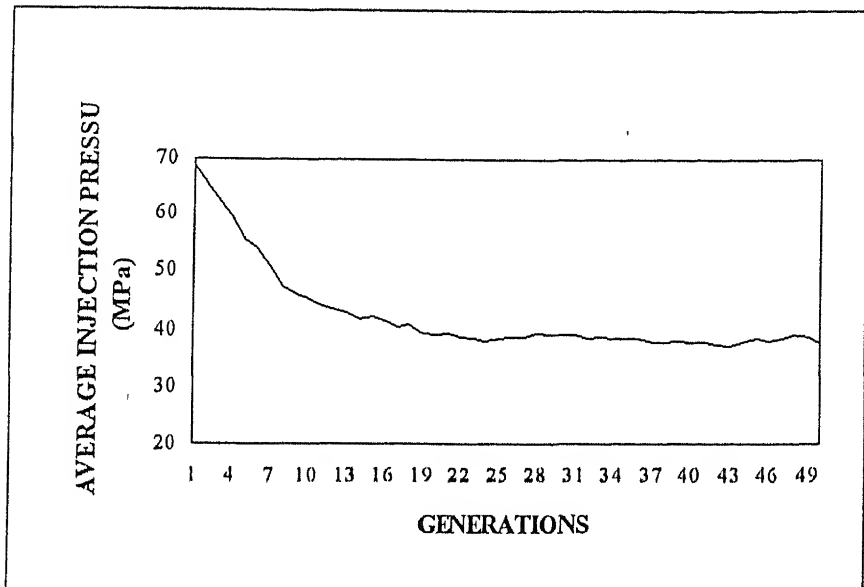


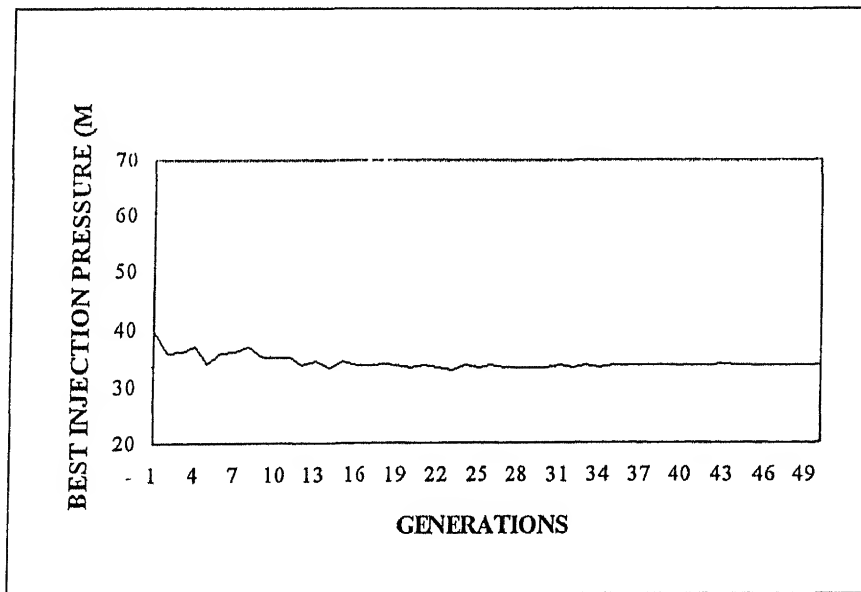
Figure 7.2.18 Convergence graph  
CCD model, Moldflow Simulator, Polystyrene Diskcady



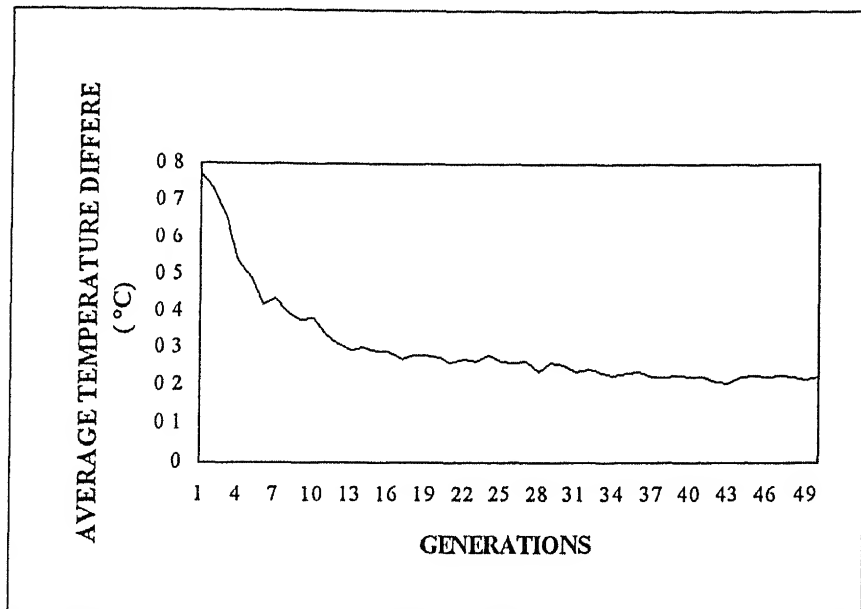
**Figure 7.2.19 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



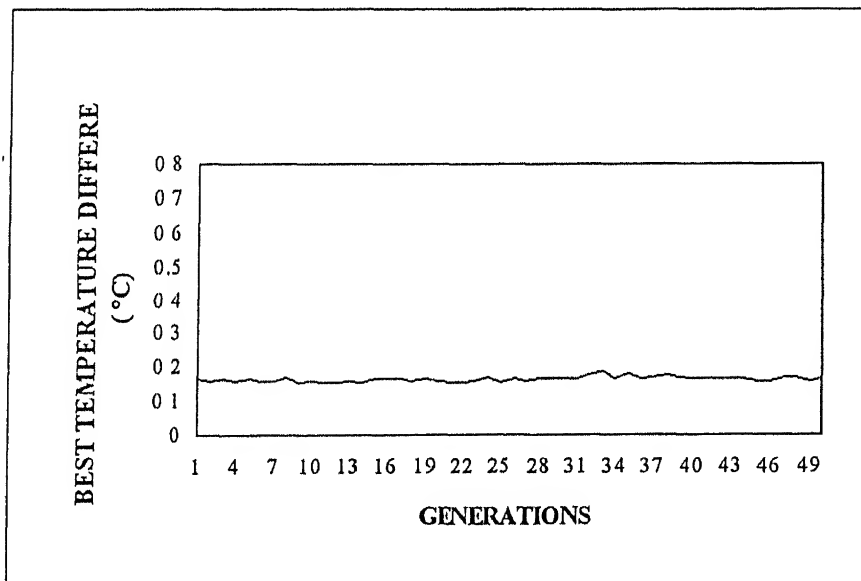
**Figure 7.2.20 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



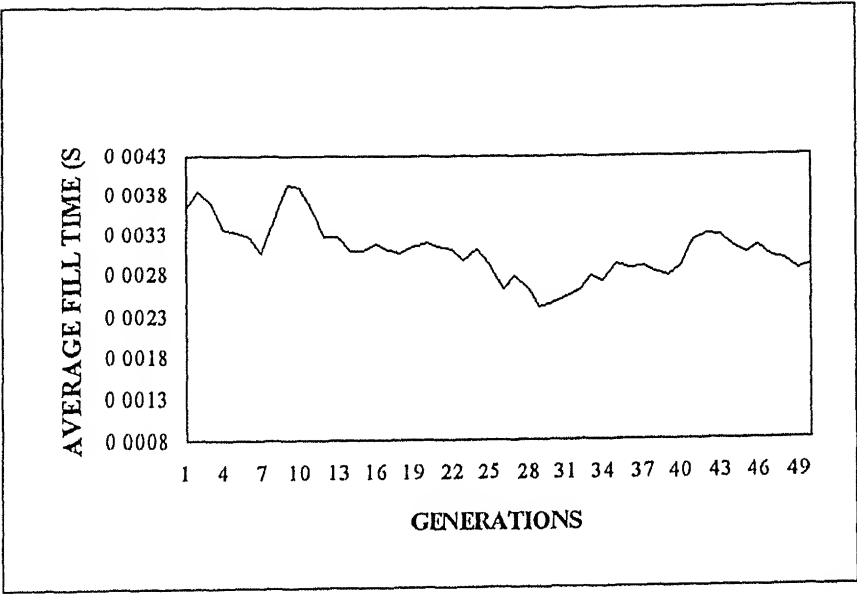
**Figure 7.2.21 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



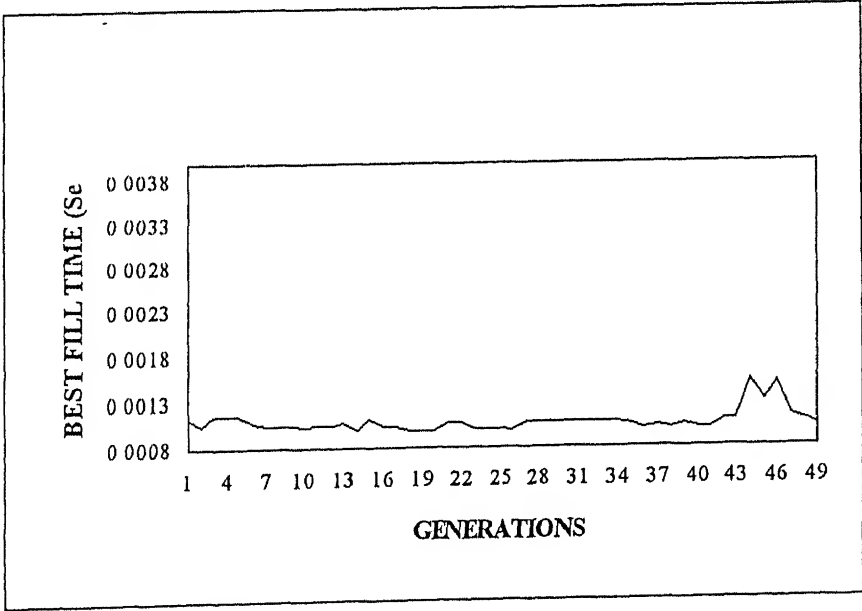
**Figure 7.2.22 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



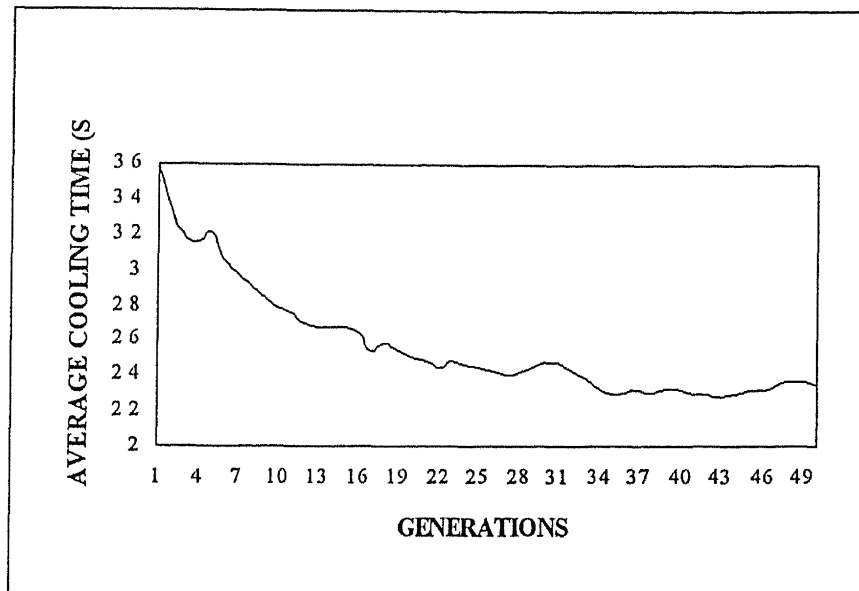
**Figure 7.2.23 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



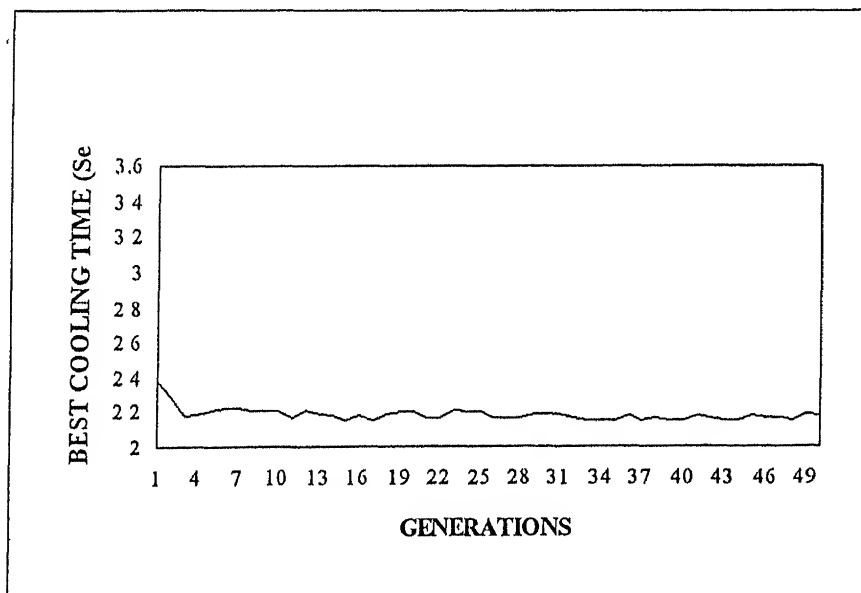
**Figure 7.2.24 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



**Figure 7.2.25 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



**Figure 7.2.26 Convergence graph**  
**Box-Behenkin model, Moldflow Simulator, Polypropylene Tape casing**



### 7.3 NSGA results

In this study total three experimental designs used to build four sets of regression models. Three from the data of Moldflow simulator and one from the data from the CMOLD simulator. Various designs build and their details are as below

- 1  $3^3$  full factorial DOE is used to develop the second-order regression models for the three responses of the Moldflow simulator for the Polystyrene Diskcady and LDPE Diskcady
- 2 CCD rotatable design is used to develop the second-order regression models for the three responses of the Moldflow simulator for the Polystyrene Diskcady
- 3 Box and Behenkin four factor design is used to develop the second-order regression models for the four responses of the CMOLD simulator for the Polypropylene Tape casing

Various second-order regression models developed are shown in the section 6.6

There are totally four sets of regression models, three sets containing three second-order regression models each (Moldflow simulator) and one set contains four second-order regression models (CMOLD simulator). Multi-criteria optimisation is attempted for these second-order regression models using NSGA. We have considered two objectives at a time for simultaneous minimisation. As there are three responses for the Moldflow simulator total of three Bi-objective problems for each set of regression models. The three Bi-objective problems are

- Injection pressure and Actual injection time
- Injection pressure and Temperature difference
- Temperature difference and actual injection time

As there are four responses for the CMOLD simulator total six bi-objective problems are tested. Various pareto diagrams resulting from the optimisation of the above problems are

shown and the pareto solutions after fifty generations are shown in the tables. The six bi-objective problems are

- Injection pressure and Fill time
- Injection pressure and Cooling time
- Injection pressure and Temperature difference
- Fill time and Temperature difference
- Fill time and Cooling time
- Temperature difference and Cooling time

### 7.3.1 Parameters used in NSGA Execution

Following GA parameter values and the limits of process variables used in execution of NSGA for the B1-objective problems of Moldflow simulator for Polystyrene Diskcady. A two level DOE is conducted to find the best combination of  $P_c$  and  $P_m$  keeping the other NSGA parameters constant. We found that the combination of 0.9 crossover probability and 0.01 mutation probability is giving the best results for hundred populaion

- *Population size* = 100
- *Pcross ( $P_c$ )* = 0.9
- *Pmute ( $P_m$ )* = 0.01
- *Dshare* = 1
- *Length of chromosome* = 24
- *Mold Temperature (min)* = 20 °C
- *Mold Temperature (max)* = 70 °C
- *Melt Temperature (min)* = 185 °C
- *Melt Temperature (max)* = 225 °C
- *Injection time (min)* = 0.0075 Sec
- *Injection time (max)* = 3 Sec

Following GA parameter values used and the limits of process variables in execution of NSGA for the Bi-objective problems of Moldflow simulator for LDPE Diskcady

- *Population size* = 100
- *Pcross ( $P_c$ )* = 0.9
- *Pmute ( $P_m$ )* = 0.01
- *Dshare* = 1
- *Length of chromosome* = 24
- *Mold Temperature (min)* = 20 °C
- *Mold Temperature (max)* = 60 °C
- *Melt Temperature (min)* = 205 °C
- *Melt Temperature (max)* = 245 °C
- *Injection time (min)* = 0.01 Sec
- *Injection time (max)* = 3 Sec

Following GA parameter values and the limits of process variables that are used in NSGA execution for the Bi-objective problems of CMOLD simulator for Polypropylene Tape casing

- *Population size* = 100
- *Pcross ( $P_c$ )* = 0.9
- *Pmute ( $P_m$ )* = 0.01
- *Dshare* = 1
- *Length of chromosome* = 32
- *Mold Temperature (min)* = 20 °C
- *Mold Temperature (max)* = 80 °C
- *Melt Temperature (min)* = 200 °C
- *Melt Temperature (max)* = 280 °C
- *Max Injection Pressure (min)* = 0 Mpa
- *Max Injection Pressure (max)* = 300 Mpa
- *Max Injection Rate (min)* = 0 cm<sup>3</sup>/Sec
- *Max. Injection Rate (Max)* = 10000 cm<sup>3</sup>/Sec

Figures 7.3.1 show the initial population of chromosomes and the population after fifty generations. Figure 7.3.2 shows the movement of the members as NSGA executes on to the non-dominated (Pareto) front for every fifth generation from randomly generated initial population to twenty fifth generation. Both these figures are for the Bi-objective problem of “injection pressure” and “actual injection time” for polystyrene diskcady. Table 7.3.1 shows the Pareto optimal solutions after fifty generations. Subsequently from the resulting solutions (Table 7.3.1) on the Pareto front the decision maker will be expected to select any solution depending his preference criteria and performance requirements. A particular specification of Mold temperature, Melt temperature and Injection time yields the corresponding values of the Injection pressure and actual injection time. Figures 7.3.3 to Figures 7.3.20 show the Pareto solutions obtained for the other Bi-objective problems.

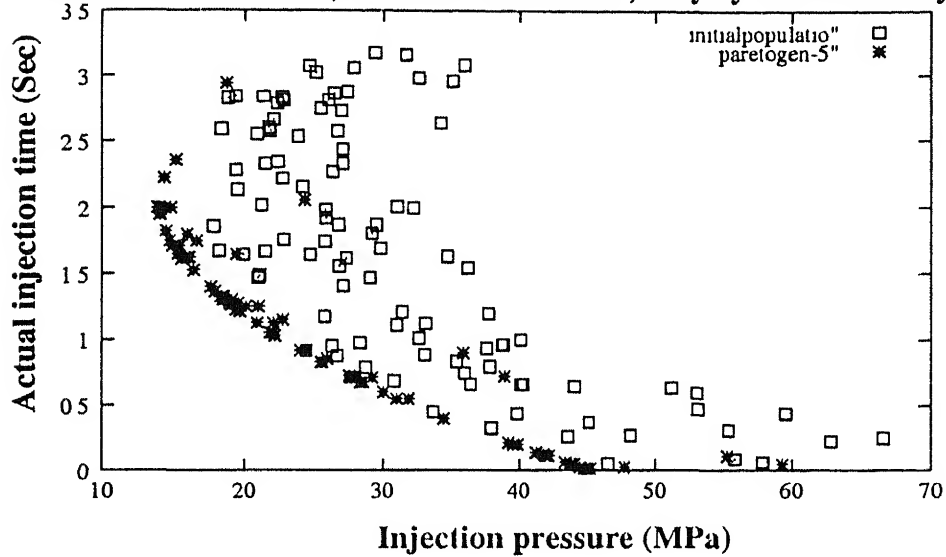
Figures 7.3.13 and Figure 7.3.14 show the solutions obtained for the Bi-objective minimisation problem of “actual injection time” and “temperature difference” after 50 generations. In this figures we can notice that there is no Pareto front and the solutions converged at the low left corner. This can be explained as follows with increase in injection time there is increase in temperature difference along the flow front. As objectives are not conflicting there is no possibility of Pareto front. As we are doing minimisation of the two objectives simultaneously the solutions converged to the low left corner of the Pareto diagram. The same observation can also be noted in the Figure 7.3.17 for the Bi-objective problem of “fill time” and “temperature difference”, which is from the results of CMOLD simulator.

Tables 7.3.2 to Tables 7.3.14 show the Pareto optimal solutions that are obtained from the execution of NSGA for the various Bi-objective problems.

The results that are obtained from the NSGA are cross checked by using the process variable values given by the NSGA for the different solutions along the Pareto front for all the cases.

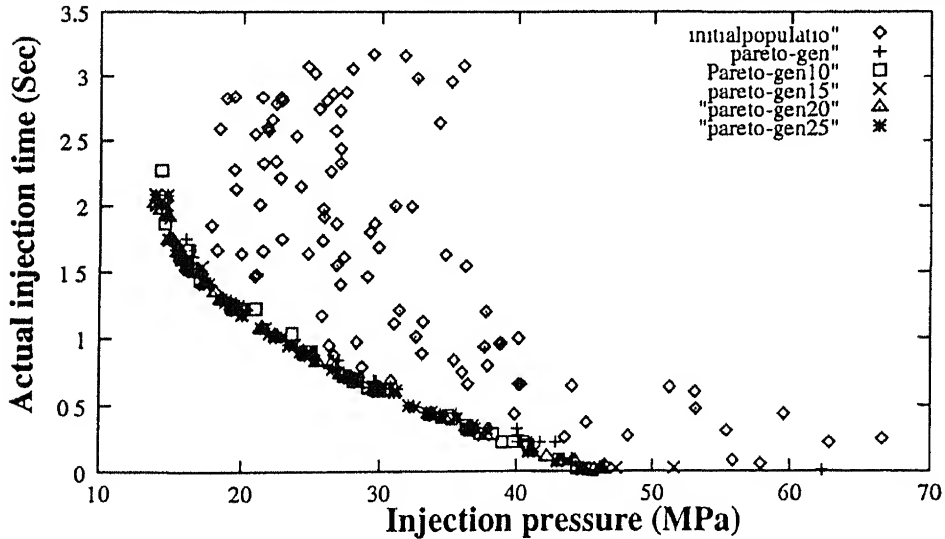
**Figure 7.3.1 Pareto solutions after 50 generations**

**3 x 3 x 3 DOE model, Moldflow simulator, Polystyrene Diskcady**

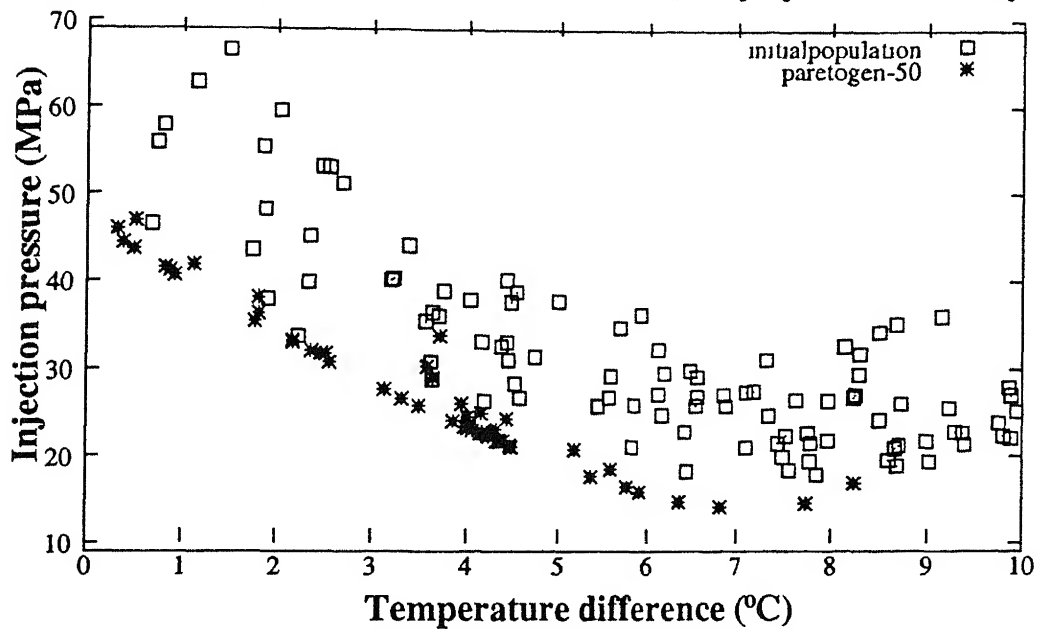


**Figure 7.3.2 Convergence of solutions to Pareto front**

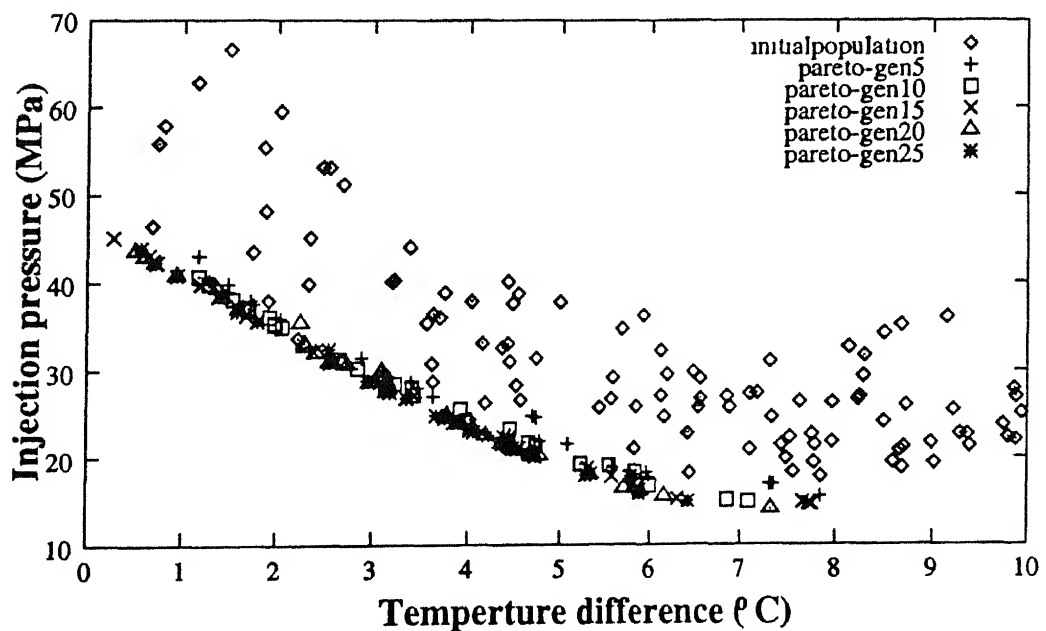
**3 x 3 x 3 DOE model, Moldflow simulator, Polystyrene Diskcady**



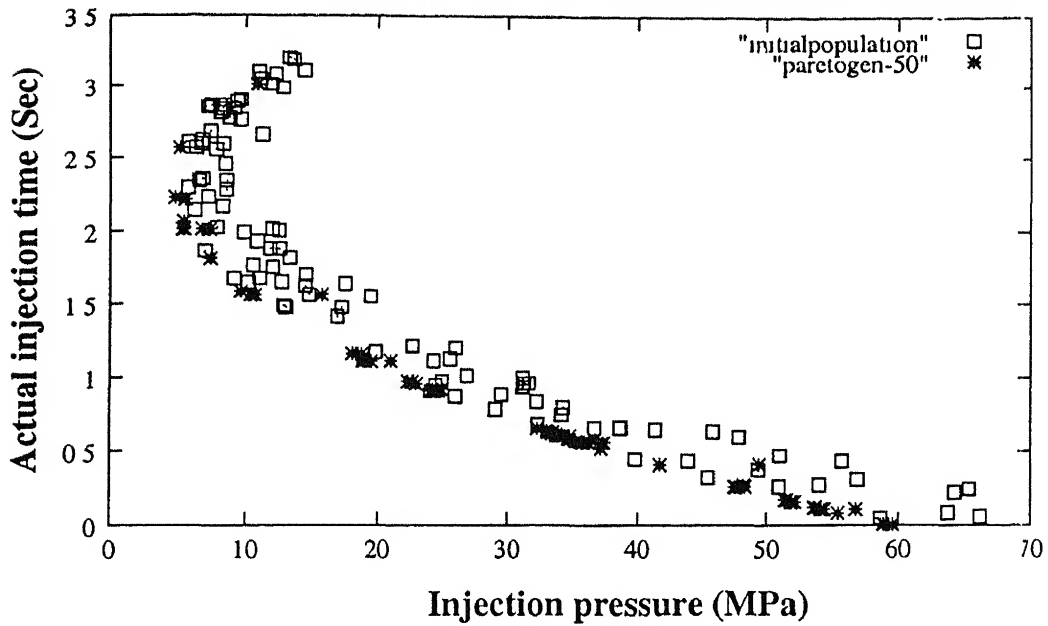
**Figure 7.3.3 Pareto solutions after 50 generations**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**



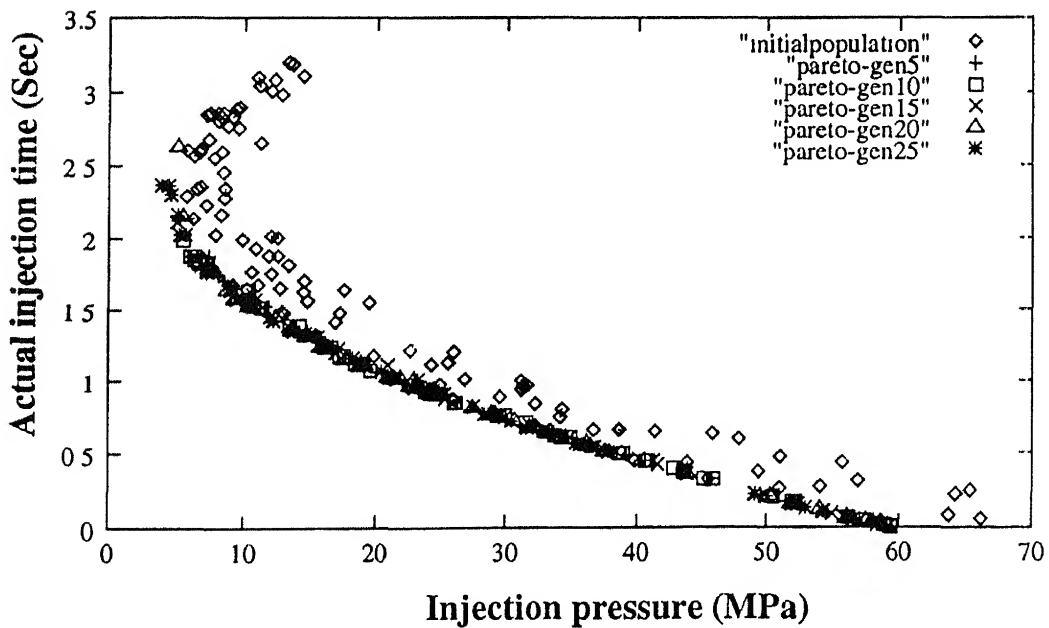
**Figure 7.3.4 Convergence of solutions to Pareto front**  
**3 x 3 x 3 DOE model, Moldflow Simulator, Polystyrene Diskcady**



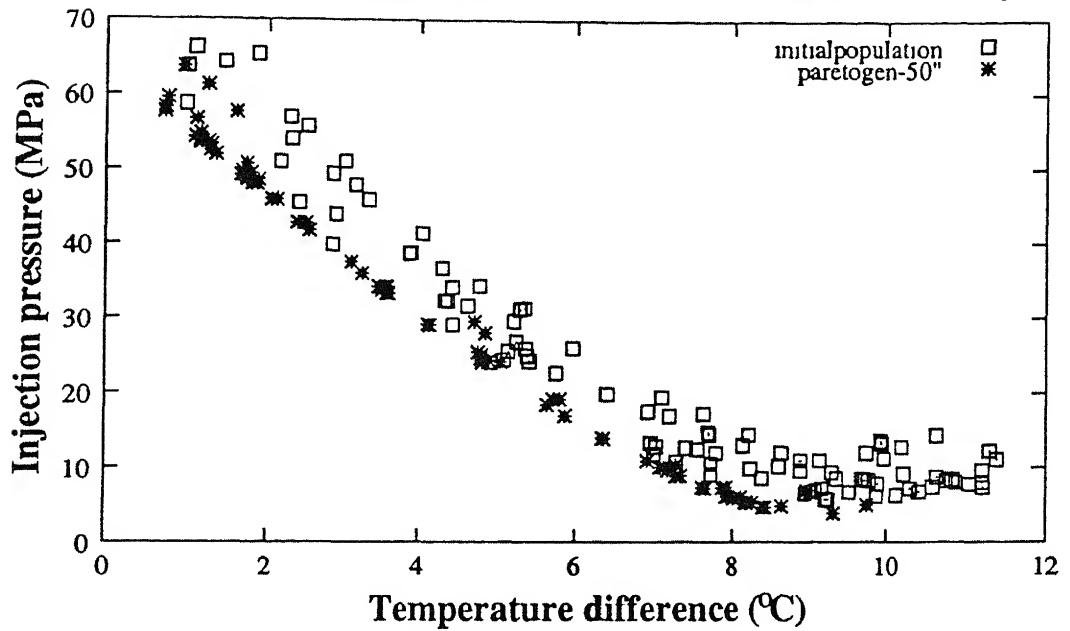
**Figure 7.3.5 Pareto solutions after 50 generations**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



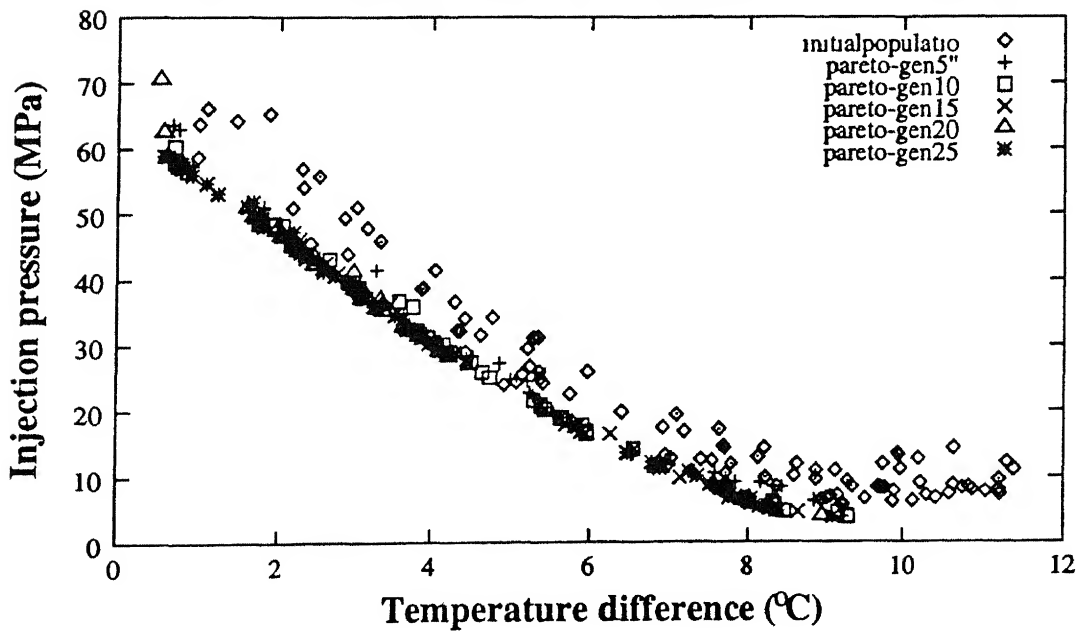
**Figure 7.3.6 Convergence of solutions to Pareto front**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



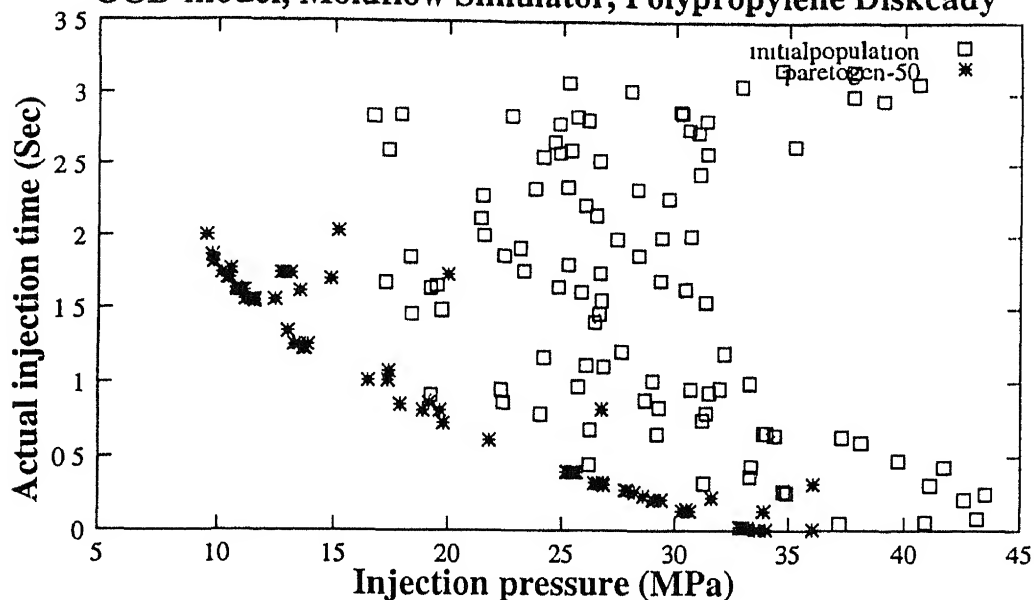
**Figure 7.3.7 Pareto solutions after 50 generations**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



**Figure 7.3.8 Convergence of solutions to Pareto front**  
**3 x 3 x 3 DOE model, Moldflow Simulator, LDPE Diskcady**



**Figure 7.3.9 Pareto solutions after 50 generations**  
**CCD model, Moldflow Simulator, Polypropylene Diskcady**



**Figure 7.3.10 Convergence of solutions to pareto front**  
**CCD model, Moldflow Simulator, Polypropylene Diskcady**

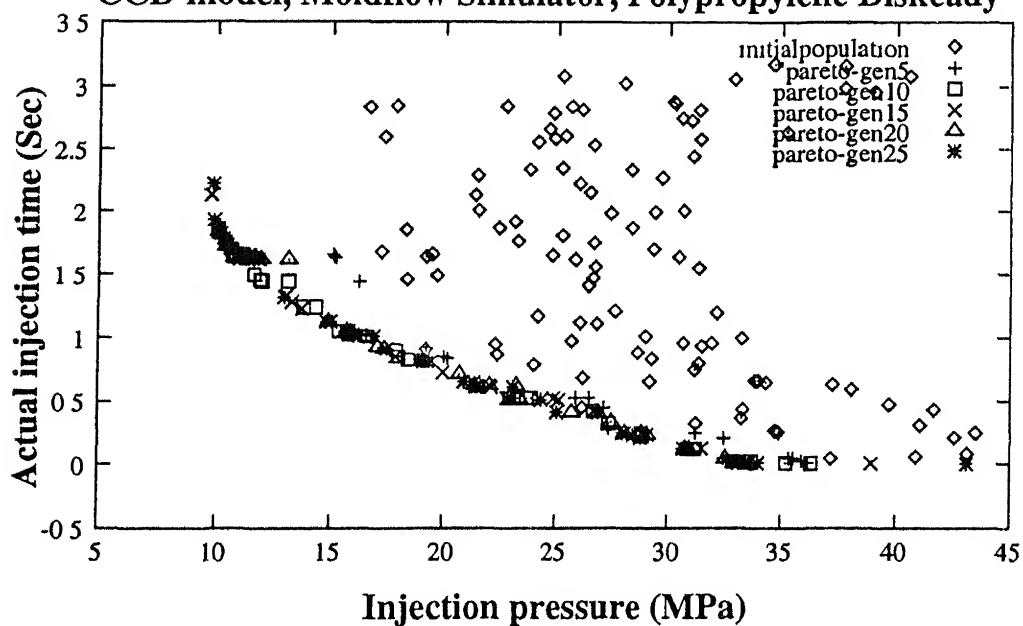


Figure 7.3.11 Pareto solutions after 50 generations  
CCD model, Moldflow Simulator, Polypropylene Diskcady

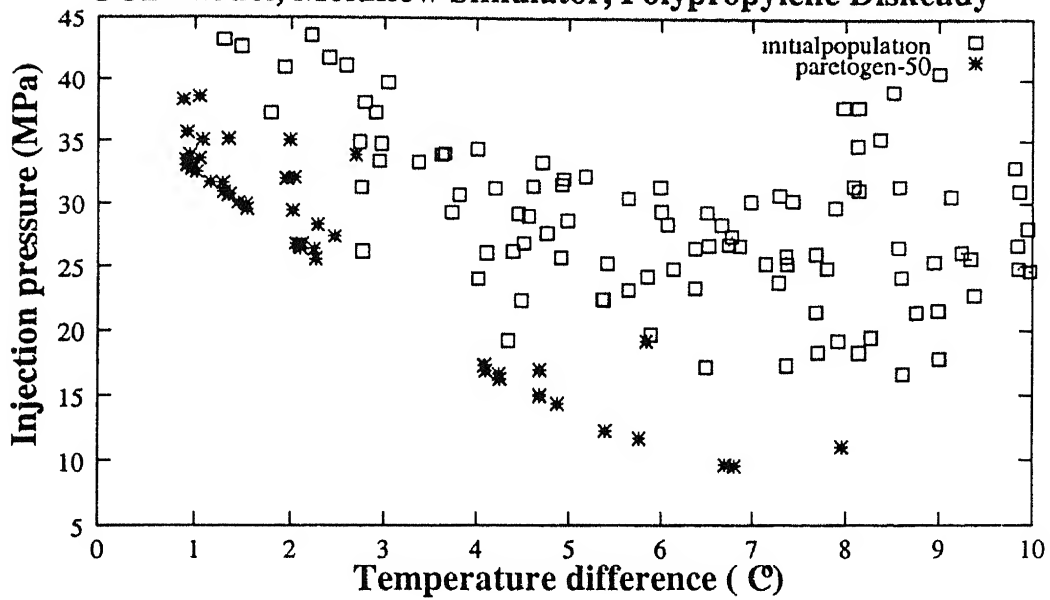
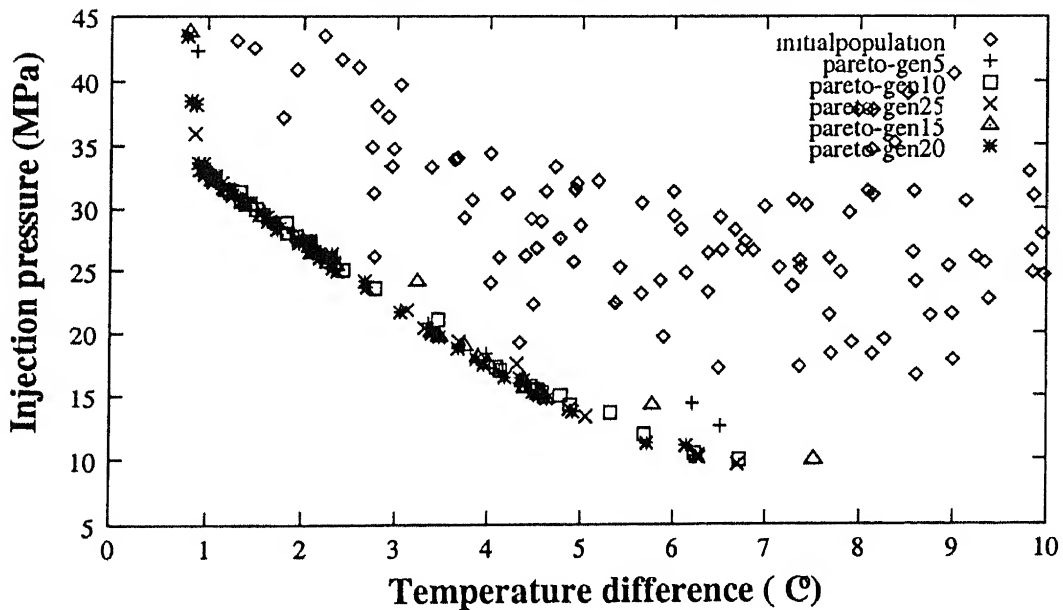
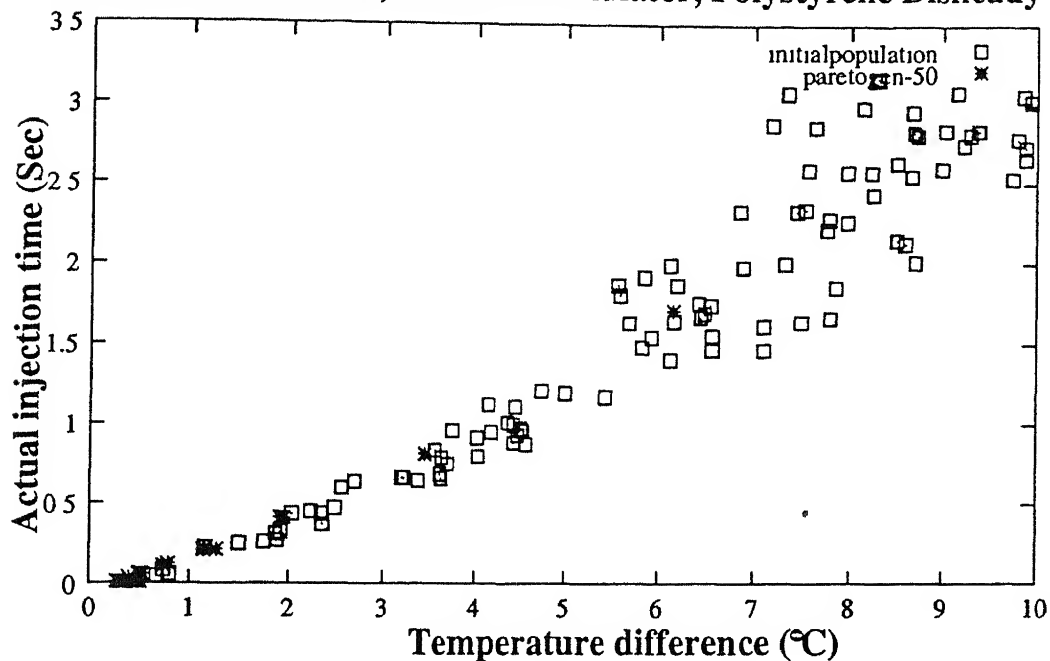


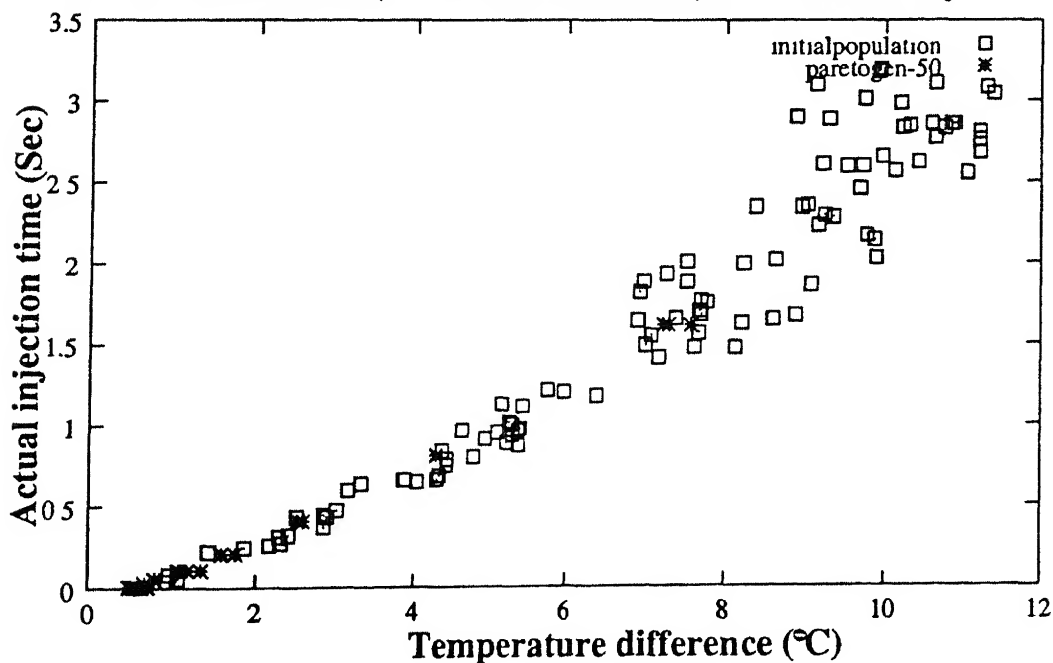
Figure 7.3.12 Convergence of solutions to Pareto front  
CCD model, Moldflow Simulator, Polypropylene Diskcady



**Figure 7.3.13 Pareto solutions after 50 generations**  
**3 x 3 x 3 DOE model, Moldflow simulator, Polystyrene Diskcady**

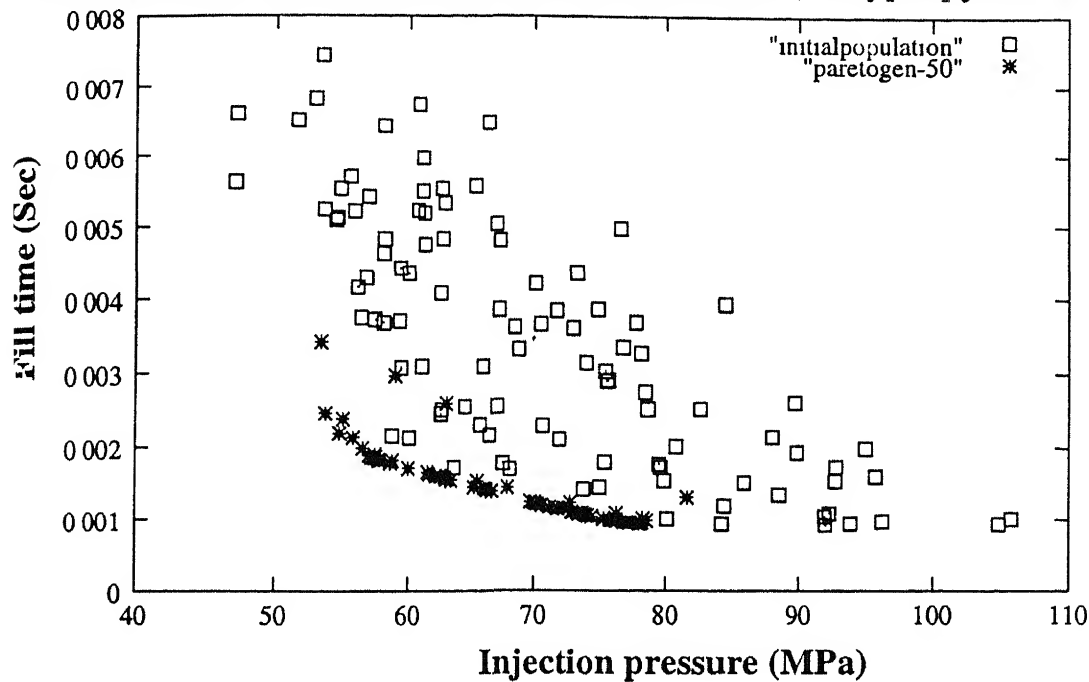


**Figure 7.3.14 Convergence of solutions to Pareto front**  
**3 x 3 x 3 DOE model, Moldflow simulator, LDPE Diskcady**



**Figure 7.3.15 Pareto solutions after 50 generations**

**$\alpha$  and Behenkin design model, CMOLD Simulator, Polypropylene Tape casing**



**Figure 7.3.16 Convergence of solutions to Pareto front**

**$\alpha$  and Behenkin design model, CMOLD Simulator, Polypropylene Tape casing**

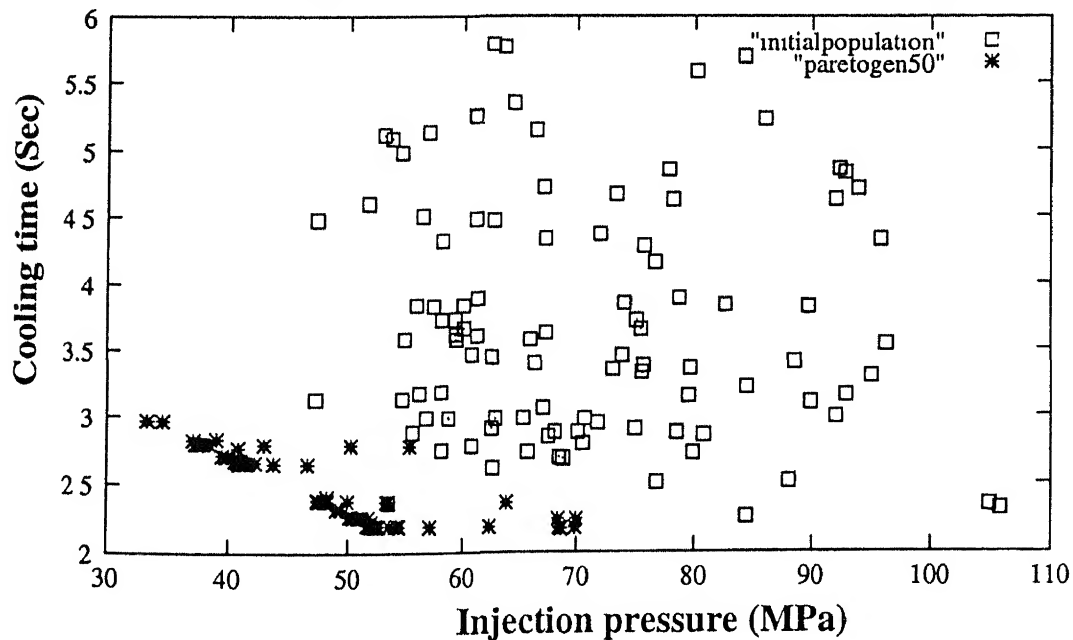


Figure 7.3.17 Pareto solutions after 50 generations

Box and Behenkin model, CMOLD Simulator, Polypropylene Tape casing

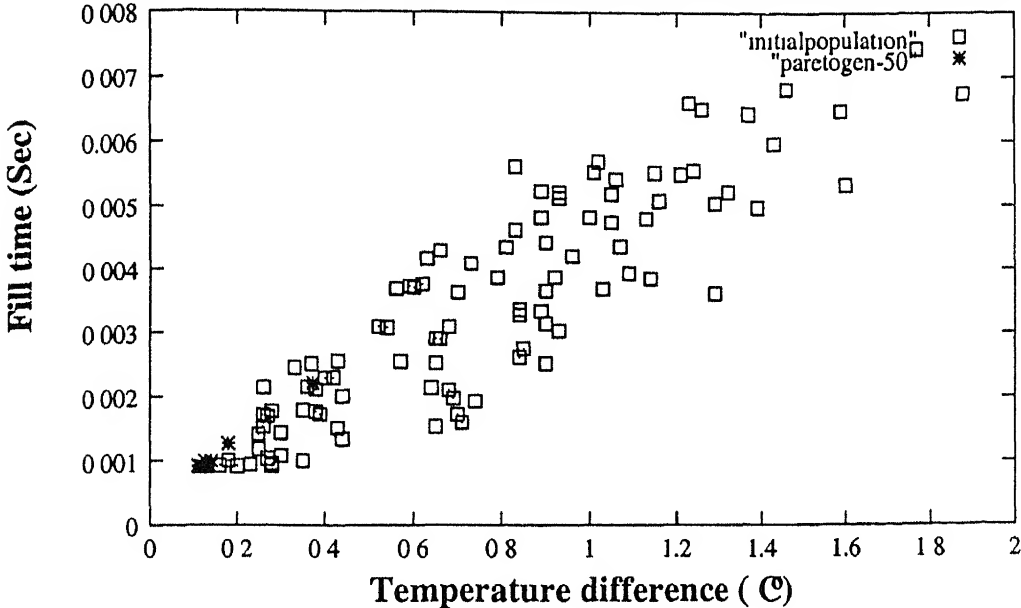
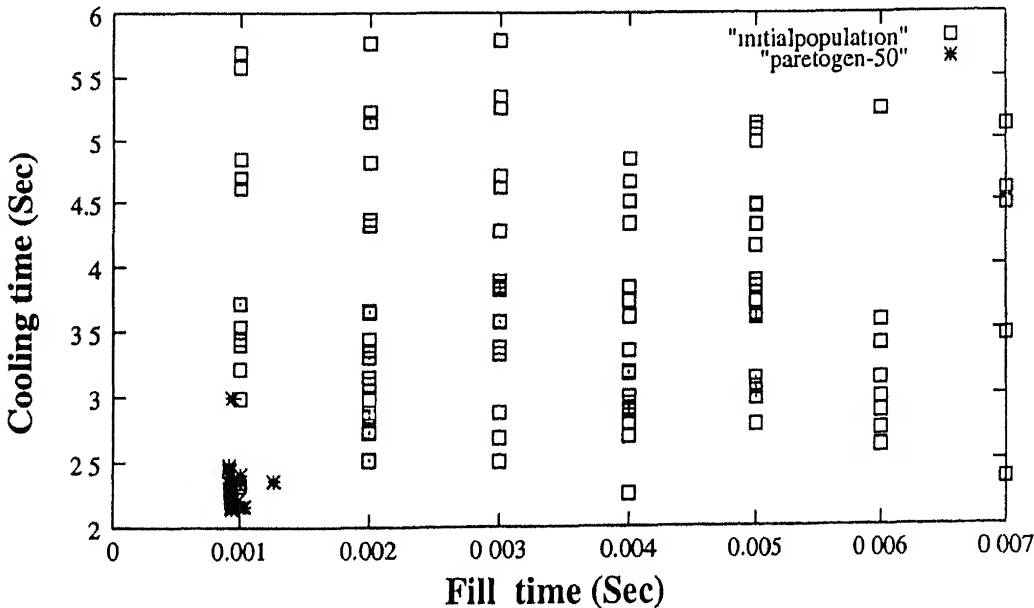


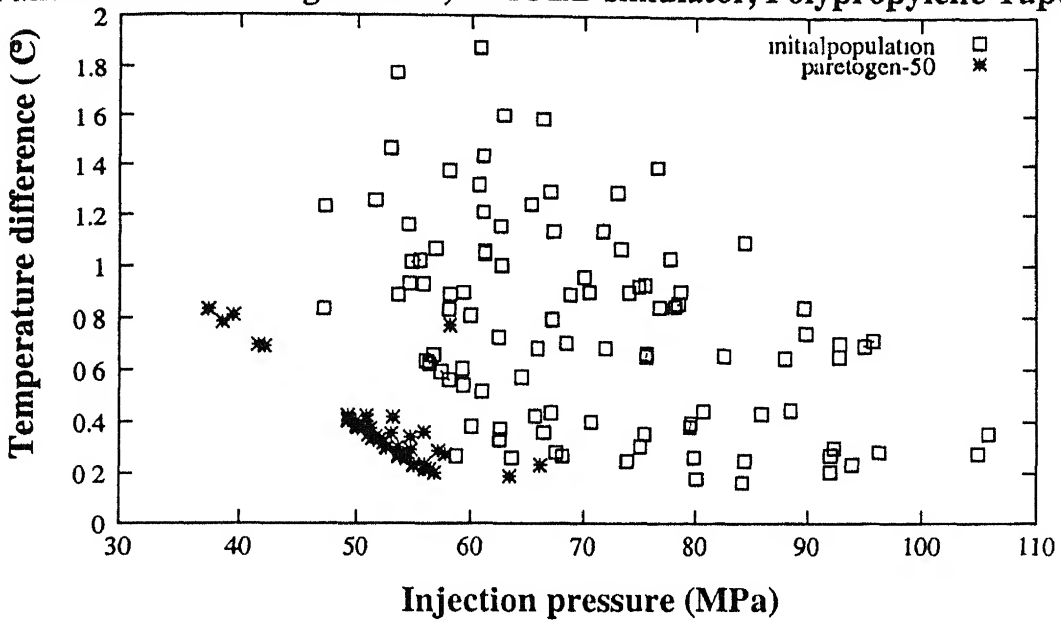
Figure 7.3.18 Convergence of solutions to Pareto front

Box and Behenkin model, CMOLD Simulator, Polypropylene Tape casing



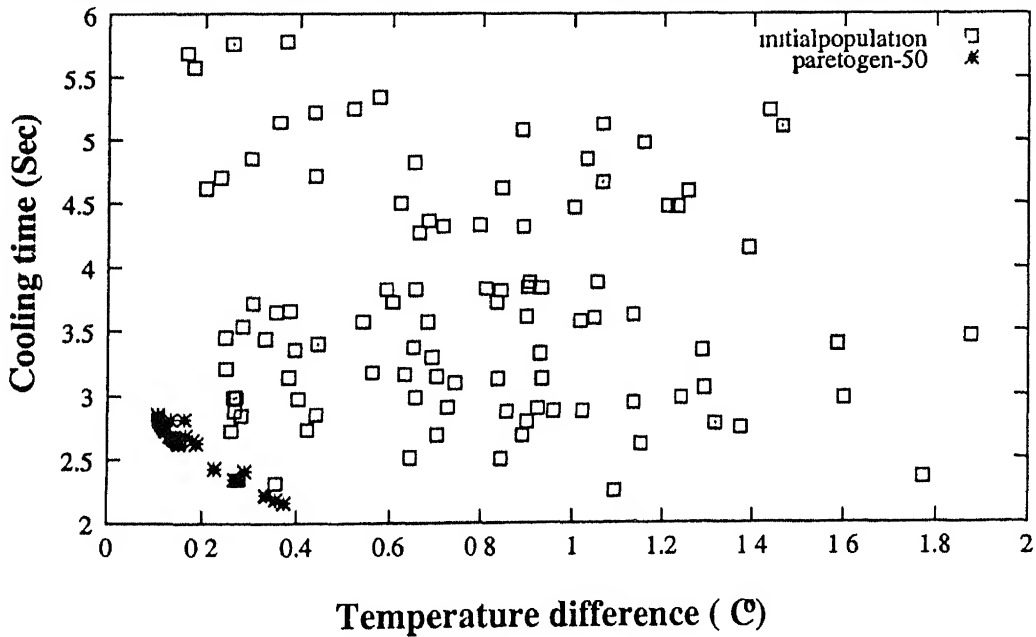
**Figure 7.3.19 Pareto solutions after 50 generations**

**Box and Behenkin design model, CMOLD simulator, Polypropylene Tape casing**



**Figure 7.3.20 Convergence of solutions to Pareto front**

**Box and Behenkin design model, CMOLD simulator, Polypropylene Tape casing**



Following notations are used in the Tables

Mold Temp = Mold Temperature

Melt Temp = Melt Temperature

Inj Time = Injection time

Inj Pres = Injection Pressure

Ac Inj Time = Actual Injection Time

Temp Diff = Temperature Difference

M Inj Pre = Maximum Injection Pressure

M Inj. Rate = Maximum Injection Rate

**Table 7.3.1 : NSGA population for process model by  $3^3$  factorial design on Moldflow Simulator for Polystyrene Diskcady**

<b>Pareto Optimal Solutions after 50 Generations</b>				
<b>Process variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Inj. Pres.</b>	<b>Ac.Inj.Time</b>
<b>°C</b>	<b>°C</b>	<b>Sec</b>	<b>MPa</b>	<b>Sec</b>
69 41	223.75	1 52	16 01	1 62246
69 41	222 18	1 05	22 04	1 123387
68 63	224 84	1 86	14 11	1 983806
68 63	202 1	0 04	59 32	0 046388
66 27	224 84	1 87	14 38	1 996091
69 8	225	1 54	15.31	1.647718
69 02	214.96	1.54	19.41	1 645565
69 41	224 84	1.71	14 48	1 822024
69 8	224 84	1 83	14 03	1 946537
69 41	224.69	0 11	41 8	0.124522
57 25	225	1 17	20 1	1.248401
69 8	219 98	1.64	16 61	1 746159
69 41	224 84	1 87	13.99	1 996299
66 27	225	2 08	14 35	2 22003
69 8	224.69	0 66	27 76	0.712058
69 8	225	1 64	14 73	1 747367
69 8	225	1 51	15 56	1 610343
69 8	225	0 2	39 2	0 212154
43 53	204 92	1 93	24 3	2 053405
69 8	225	1.15	19 35	1.223897
69 8	224 84	1.83	14 03	1.946537
69 8	224.69	0 66	27.76	0.712058

69 02	224 84	1 87	14 03	1.996275
58 63	224 69	0.79	25 93	0.849352
69 41	225	0 51	31 01	0.549735
69 8	225	0 66	27 6	0.712142
69 41	225	0.77	25 5	0.824547
69 8	224 69	1.13	19 65	1.211341
69 8	225	1 87	13 88	1.996365
69 41	223 75	1 6	15 44	1.709658
69 8	224 84	1 87	13 94	1.996323
69 41	224 84	0 77	25 58	0 824505
69.8	225	0 66	27 6	0 712142
69 8	224.69	1 27	17 9	1 360988
31 76	225	0.66	29 24	0.710341
69 8	225	0 98	21 75	1 049235
69 02	224 69	1 05	20 88	1.124013
63 53	225	0.1	42 17	0.112369
63 14	225	2 21	15.15	2 35647
69 8	225	0 77	25 47	0 824542
56 86	224 84	1 69	15 96	1 796232
68 63	225	0 18	39 59	0 199705
69.8	225	1 54	15 31	1 647718
69 41	225	0 02	44 47	0 024501
67.84	225	0 56	30 02	0 599754
69 8	223.59	1 22	19 07	1 298358
69 8	224.84	1 83	14 03	1 946537
69 41	225	0 63	28 37	0 674676
68 82	224 69	1 31	17.61	1 398367
69 41	224 69	0 11	41 8	0.124522
69 41	224.53	0.04	44 04	0 049405
69 8	225	0.05	43 37	0 06202
67 84	224 69	1 24	18 49	1 323542
69 8	224 69	1 18	19 03	1 26123
63.53	225	1 52	16 14	1 622505
69 8	225	0.1	41 94	0 112072
69 41	224 06	0 66	28.13	0 711902
69 8	225	1 64	14 73	1.747367
63 14	224 84	0 18	39 9	0 19988
69 41	225	0.85	23.97	0 911942
69 8	224 84	2 77	18 72	2 940907
69 41	225	0 37	34 46	0 399748

69 8	223 43	0 51	31 87	0 549315
68 63	225	0 18	39 59	0 199705
69 41	224 84	1 83	14 08	1.946515
70	224 53	1 19	18 93	1 273663
69 8	225	0 12	41 24	0 137095
69 8	224 69	0 68	27 52	0 724549
69 41	224 69	1 24	18 34	1 323575
69 8	225	0 96	22 13	1 024276
69 8	225	1 87	13 88	1 996365
69 41	224 84	0 04	43 84	0 049488
69 41	204 92	0 1	55 28	0 108956
69 8	224 69	0 01	45 03	0 011877
69 8	225	0 1	41 94	0 112072
63 14	225	0 85	24.42	0 911917
63 53	224 53	1 19	19 52	1 273505
69 41	223 43	0 51	31 89	0.549328
69 8	219 98	1 08	22 69	1 147845
68 24	203 51	0 84	35.89	0 896318
62 16	224 69	0 68	28 01	0.724603
69 41	204 61	0 68	38 91	0 721489
62 55	224 84	1 87	14 82	1 995798
70	224 84	1 87	13 91	1.996334
68 63	225	1 22	18 56	1.298705
69 41	224 69	1 43	16 4	1 523023
68 63	225	1 22	18 56	1.298705
68 82	224 69	1 31	17 61	1 398367
69 8	219 98	0 02	47.73	0 023268
69 41	224 69	1 13	19 68	1 211337
66 67	225	0 98	22 01	1 049217
31 76	225	0 01	45 25	0 011831
69 41	224 69	0 63	28 54	0.674592
69 8	225	0 05	43 37	0 06202
69 61	224 69	1 19	18 9	1 273699
69 8	225	0 01	44 82	0 011961
68 24	225	0 04	43 78	0.0496
69 8	225	1 22	18 45	1 298726
44 71	225	1 17	20 96	1 247393
69 8	225	1 6	14 93	1.710002

70	224 53	0 03	0 38	44 38546
70	224 84	0 34	1 77	35 43248
69 22	225	0 98	4 33	21 79934
70	224 84	0 9	4 01	23 17444
63 73	224 84	0 93	4.31	23 06239
70	224 53	0 05	0 49	43 65834
57 45	224 84	1.12	5 17	20 75549
44 9	224 53	0 14	1 12	41 85003
70	224 84	0.9	4 01	23 17444
70	224 84	0 93	4 14	22 57623
44 9	224 84	0 66	3 64	28 97431
66 86	224 53	0 5	2 52	31 69531
70	224 84	0.93	4 14	22 57623
69 8	224 84	0 85	3 85	24 01798
63 53	222 33	0.9	4 15	24 92936
70	224 84	0 43	2.17	33 03829
69.8	224 84	0 96	4 23	22 20458
69 8	224 53	0 95	4 18	22 54996
68 43	225	0 98	4 35	21.86379
70	224.84	0 52	2 56	30 78458
68.43	224 84	0 99	4 39	21 75392
70	224.84	0.52	2 56	30 78458
69 8	223 9	0 95	4 17	22.85628
70	225	0.71	3.31	26 61609
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69 8	224.84	0.99	4 35	21.63962
69.8	224 84	0.85	3 85	24 01798
70	224 84	0 91	4 06	22 97284
70	224.53	0 05	0 49	43.65834
69.8	224 53	0.12	0 82	41 53798
66 86	224 84	0 49	2 47	31 79445
70	219 82	1 42	5 58	18 45788
70	224 84	0.76	3.49	25 76486
70	224.84	0 52	2 56	30 78458
70	224 53	0 05	0 49	43 65834

69 8	224 37	2 59	8 24	16 87083
70	224 84	0 9	4 01	23 17444
63 53	224 84	0 85	4	24.47739
70	219 82	0 35	1 81	38 12025
70	224 84	0.43	2 17	33 03829
70	204 76	0 9	3 71	33 75562
63 73	223 59	0 01	0 32	45 942
70	225	0 98	4 31	21 73409
70	224 84	0.76	3 49	25 76486
70	224 84	0 76	3 49	25 76486
70	224 84	0 76	3.49	25 76486
69 8	224 84	0 93	4 14	22 59219
69 8	224 69	1 49	5 91	15 86614
70	224 84	0 9	4 01	23.17444
70	219 51	0 05	0 51	46.91023
70	224 84	0 93	4 14	22 57623
66 86	223 59	0 34	1 81	36.33747
70	224 84	0 9	4 01	23.17444
70	224 53	1 03	4.46	21 22575
69.8	224.53	0.95	4.18	22.54996
70	224.84	1.65	6 36	14.6968
70	214 18	0.82	3 58	30 25324
70	224.84	1 03	4 47	21 07755
70	224.53	0 48	2 37	32 07169
70	224 84	0 9	4 01	23 17444
70	224 84	0 9	4.01	23 17444

**Table 7.3.3 : NSGA population for process model by 3<sup>3</sup> factorial design on Moldflow Simulator for Polystyrene Diskcady**

<b>Pareto Optimal Solutions after 50 Generations</b>				
<b>Process Variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Temp. Diff.</b>	<b>Ac.Inj. Time</b>
°C	°C	Sec	°C	Sec
70	207.9	0.38	1.91	0.409253
70	220.45	0.01	0.29	0.01084
70	211.67	0.01	0.33	0.009351
70	208.37	0.01	0.34	0.009014
70	205.08	0.01	0.34	0.008798
70	215.12	0.01	0.31	0.009834
44.9	212.29	0.01	0.48	0.010478
69.22	221.86	0.01	0.29	0.011214
70	206.18	0.01	0.34	0.008857
70	195.98	0.01	0.34	0.008827
57.45	207.59	0.01	0.42	0.009858
70	215.43	0.01	0.31	0.009884
69.8	205.08	0.01	0.34	0.008817
70	221.86	1.6	6.15	1.709221
68.43	207.59	0.01	0.35	0.009096
70	216.06	0.01	0.31	0.009989
70	207.59	0.01	0.34	0.008952
70	207.43	0.2	1.14	0.209135
70	197.55	0.01	0.35	0.008757
70	211.35	0.38	1.93	0.409591
70	216.37	0.01	0.31	0.010042
70	220.45	0.01	0.29	0.01084
70	220.14	0.01	0.29	0.010772
70	205.39	0.01	0.34	0.008813
70	220.45	0.76	3.45	0.310943
70	211.2	0.05	0.54	0.059355
70	211.2	0.01	0.33	0.009296
70	208.69	0.01	0.34	0.009041
70	215.75	0.01	0.31	0.009936
70	206.18	0.01	0.34	0.008857
70	221.24	0.05	0.5	0.061074
70	207.59	0.01	0.34	0.008952
70	209.94	0.01	0.33	0.00916
70	215.27	0.1	0.74	0.109971

70	196 61	0.01	0 35	0 008796
70	216 22	0 01	0 31	0 010015
69 22	222 49	0 01	0 28	0 011362
70	215 43	0 01	0 31	0 009884
63 73	215 12	0 01	0 36	0 010279
70	216 06	0 11	0 79	0 122612
57 45	206 65	0.2	1 27	0 20985
70	196 61	0 01	0 35	0 008796
70	216 22	0.01	0 31	0 010015
70	215.12	0 01	0 31	0 009834
70	207 59	0 01	0 34	0 008952
70	216 37	0 38	1 95	0 41032
70	216 37	0 01	0 31	0 010042
70	205 08	0.01	0 34	0 008798
70	211 67	0.01	0 33	0.009351
70	207 59	0 01	0 34	0 008952
70	215 43	0 01	0 31	0 009884
70	216 22	0 01	0 31	0 010015
68 43	208.84	0.01	0.35	0.009196
70	207 59	0.01	0 34	0 008952
70	220.45	0 01	0.29	0 01084
70	207 59	0 01	0 34	0 008952
70	215 59	0 01	0 31	0 00991
69 8	220 45	0 01	0 29	0 010854
69 22	221.86	0 01	0 29	0 011214
70	211 82	0 01	0 33	0 009371
70	195 35	0 01	0 34	0 008863
70	220 45	0 01	0 29	0 01084
66 86	216 37	0 01	0 33	0 010276
69 8	216 22	0.01	0 31	0 010031
70	206 18	0 01	0 34	0 008857
69 8	205.08	0 01	0 34	0 008817
70	220 45	0 03	0 4	0 035871
70	216 06	0.01	0 31	0 009989
70	208.84	0 01	0 33	0 009055
70	211 2	0 2	1 15	0 209491
70	215.75	0.01	0 31	0 009936
70	218 57	0 01	0 3	0 010449
70	207 59	0 01	0 34	0 008952
70	205.08	0.01	0.34	0 008798

70	216.06	0 01	0.31	0 009989
69 22	221 86	0.01	0 29	0 011214
63 73	205 08	0 01	0 38	0 009348
69 8	216 22	0 01	0 31	0 010031
70	207 59	0 01	0 34	0.008952
70	187.51	0 01	0 33	0.009682
38 63	209 31	0 01	0 51	0 010211
70	208 84	0 01	0 33	0 009055
70	215 75	0 01	0 31	0 009936
70	211 35	0 05	0.54	0 059374
70	204 14	0 1	0 75	0 10887
70	196 61	0 01	0 35	0 008796
70	207 43	0 01	0 34	0 00894
70	211 67	0 01	0 33	0 009351
70	215 43	0.01	0 31	0 009884
70	208 69	0 01	0 34	0 009041
66 86	196 61	0 01	0 36	0 009133
70	208.22	0 01	0 34	0 009001
70	210 88	0 01	0 33	0 00926
70	216 22	0 01	0 31	0 010015
70	217 47	0 01	0 3	0 010239
70	220 45	0.01	0.29	0 01084
70	217 47	0.05	0 52	0 060298
70	220 61	0.01	0 29	0.010875
70	207 59	0 01	0 34	0 008952
70	215 75	0 01	0 31	0 009936

**Table 7.3.4 : NSGA population for process model by 3<sup>3</sup> factorial design on Moldflow Simulator for LDPE Diskcady**

<b>Pareto Optimal Solutions</b>				
<b>Process Variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Inj. Pre.</b>	<b>Ac. Inj. Time</b>
°C	°C	Sec	MPa	Sec
58.9	245	0.1	54.17	0.108163
39.14	244.84	0.85	24.4	0.909676
29.57	244.84	1.46	10.64	1.561245
33.8	244.53	0.61	33.01	0.646383
38.35	244.84	0.24	47.66	0.258123
41.18	245	1.49	9.6	1.586937
38.98	244.84	0.08	55.43	0.082818
41.49	245	0.85	24.27	0.909734
56.86	245	0.01	58.86	0.007916
28.31	224.76	1.46	15.66	1.563674
51.69	244.69	0.16	51.4	0.170729
38.04	238.73	1.04	20.96	1.11126
41.49	244.84	0.24	47.6	0.258187
38.98	244.69	2.09	4.77	2.226992
37.88	244.69	0.16	51.55	0.170479
37.88	243.59	1.04	19.48	1.110447
38.98	244.84	0.08	55.43	0.082818
30.51	243.59	2.07	5.53	2.214072
58.9	245	0.1	54.17	0.108163
41.96	239.82	0.55	36.72	0.584733
20.94	241.71	1.89	7.34	2.012984
37.88	244.69	0.16	51.55	0.170479
21.1	244.84	0.24	48.33	0.257771
38.35	245	0.57	33.98	0.608846
31.45	245	0.1	54.41	0.10771
31.45	245	0.85	24.67	0.909358
51.06	245	0.85	24.06	0.910092
31.45	244.22	0.87	24.58	0.922039
21.1	244.84	1.89	6.76	2.012344
51.22	244.84	0.01	58.88	0.007864
49.02	243.43	2.4	5.12	2.567186
36.16	244.69	0.54	35.51	0.571252
38.04	244.84	0.6	33.18	0.633925
40.39	245	0.12	53.62	0.12038

41 18	245	0 57	33 9	0 608929
41 18	244 84	1 89	5 33	2 013674
32.08	244 84	0 6	33 4	0 633745
40 39	245	0 85	24 31	0 909692
32 39	245	0 57	34 2	0 608669
41 65	244 22	0 87	24 17	0 922424
28 94	245	0 39	41 77	0 408168
41 18	244 84	0 91	22 57	0 972432
41 65	244 69	0 12	53 73	0 120454
41 18	245	1 49	9 6	1 586937
38 98	245	0 85	24 36	0 90964
41 49	245	0 01	58 86	0 007702
37 41	245	0 57	34 01	0 608818
34 59	245	1 09	18	1 160183
41 02	244.84	0 9	22 92	0 95989
52 63	244.69	0 58	33 4	0 62186
47 61	244 53	0 6	33 07	0 634272
58 9	244 84	0 91	22 26	0 973125
49 18	245	0.55	34 65	0 5841
41.33	244 69	0.57	34.02	0.608991
21 1	245	0 57	34 77	0 608335
41 18	245	0 57	33 9	0 608929
37 1	244.22	1 46	10 36	1 561785
21 1	244 84	0 01	59 56	0 007446
41 02	244.84	0 54	35 3	0 571363
41 49	244 84	0.9	22 9	0 959908
41 8	243.75	0 6	33 48	0 634236
47 61	244 84	1 04	18 78	1 110621
28 31	239 98	0 1	56 77	0 108415
48.86	244 69	0 53	35 67	0 559083
38.98	245	0 01	58 9	0 007668
56 71	244 84	0 24	47 52	0 258498
31 14	244 84	1 07	18 81	1 13499
37 88	243 59	0 01	59 56	0 007883
41 65	245	0 55	34 78	0 583882
41 49	245	1 04	18 92	1 110329
37 1	245	0 53	35 81	0 558693
30 67	244 37.	0.53	36 29	0 558625
51 06	245	0 57	33 74	0 609221
41 18	245	0 15	51 91	0 157962

51 06	245	0 15	51 83	0 158138
41 49	245	0 85	24 27	0 909734
22 04	245	1 09	18 74	1 159631
34 59	244 84	1 46	10 34	1 561519
36 63	244 69	0 58	33 72	0 621381
44	224 92	0 39	49 43	0 410452
33 49	244 69	1 7	7 35	1 812408
51 22	244 69	0 54	35 2	0 571683
37 1	245	0 49	37 18	0 521109
41 49	244 69	0 62	32 27	0 659121
31 61	245	0 15	52 15	0 157791
46 67	241 08	1 93	5 44	2 065036
41 65	245	0 15	51 9	0 15797
34 59	244 84	1 46	10 34	1 561519
52 16	239 98	0 53	37 42	0 559935
25 96	244 22	0 87	24 87	0 921832
39 61	244 84	1 89	5.42	2 01357
30 51	241 86	0 53	37 26	0 559042
39 29	242 18	0 26	48 23	0 271103
58 9	244 84	0 91	22.26	0.973125
39 14	244 84	0.85	24 4	0 909676
27.06	245	0 53	36.22	0 558409
41 49	245	0.54	35 23	0.571347
41 18	244 53	0 16	51 55	0 170566
37 88	244 69	0 16	51 55	0 170479
32 08	244 69	2 81	10 84	3 005249

**Table 7.3.5 : NSGA population for process model by 3<sup>3</sup> factorial design on Moldflow Simulator for LDPE Diskcady**

Pareto Optimal Solutions after 50 generations				
Process Variables			Responses	
Mold Temp. °C	Melt Temp. °C	Inj. Time Sec	Temp. Diff. °C	Inj. Pre. MPa
59 84	244 37	1 24	6 34	13 89499
60	245	0 57	3 5	33 73152
58 59	245	1 45	7 16	9 658441
58 59	244 69	0 85	4 82	24 10034
53 57	245	0 28	2 12	45 84569
59 84	243 27	0 14	1 27	53 21534
58.59	245	0 22	1 73	48 55837
60	243 27	1 12	5 87	16 95129
59 84	245	0 56	3 45	34 17725
53 57	245	0 23	1 86	47 97754
49 8	244 84	0 85	5 05	24 12668
39 76	239 98	0 75	4 72	29 45504
53 57	245	0 56	3 58	34 16594
59 84	245	1 73	8 01	5 864067
57 33	239 98	0 22	1.73	50 66452
59 84	244 69	1 89	8 43	4.66:605
59.84	245	0 1	1 08	54 18497
58.59	245	0.51	3.24	35 98876
59.53	243 9	0.22	1 72	49 03319
53 73	243 27	1.44	7 26	10 357
59 84	244.69	1 89	8 43	4 666605
57.02	245	1 72	8 1	6 039097
58.59	243 27	0.85	4 8	24 56144
60	243 27	1 45	7 06	10.04894
59.84	245	2 47	9 75	5 010248
58.27	245	0 12	1 16	53 58505
58 9	244 84	1 8	8 25	5 264582
60	244 37	1 24	6 34	13 89387
60	243 43	1 07	5 64	18 41049
58 59	245	1 5	7 32	8 89762
59 84	245	0.15	1 33	51 90136
58 59	240 76	0 85	4 76	25 38284
59.84	245	0 12	1 14	53 60911
58 27	245	0.37	2 54	41 76141

59 84	245	0 21	1 65	49 12126
59 84	245	0.14	1 27	52 4673
39 29	239 82	1 8	8 96	6 957197
52 31	245	0 12	1 23	53 53292
54 98	245	1 87	8 64	4 809429
58 59	244 84	0 28	2 05	45 94376
49 49	245	0 02	0 71	58 20898
59 84	243 9	0 22	1 71	49 03756
59 84	243 27	0 14	1 27	53 21534
59 84	239 67	0 05	0 74	59 50431
59 53	244 37	0 12	1 14	53 87811
59 84	243 9	0 6	3 6	33 24719
60	245	1 87	8 4	4 686086
59 84	244 84	1 71	7 93	6 137174
60	245	0 14	1 27	52 46986
60	224 92	0 09	0 94	63 67374
57 02	244 69	0 48	3 1	37.49955
57 49	245	0 03	0 7	57 67107
58 59	240 76	0 85	4 76	25 38284
58.59	245	0.28	2 05	45 87907
58 59	243 27	1 45	7 11	10 06718
59 84	244 84	1 62	7 64	7.240117
59.84	244.53	1.8	8.19	5 303533
59.84	244.69	1.89	8 43	4 666605
59 84	244 84	0 7	4.11	29 08792
57 96	245	0 21	1 68	49 09664
59 84	245	0 22	1 72	48 57517
59 84	245	2 25	9 32	3 885122
49 8	233 24	0 85	4 86	27 96214
59 84	245	0 56	3 45	34 17725
59.84	245	1 5	7 27	8 880527
58 75	245	0 56	3 47	34.1703
59 06	245	1 38	6 9	10 89333
57 02	239 98	1 08	5 71	19 1377
58.59	240 76	0 87	4 81	25.01153
60	244 84	1 6	7 6	7 390571
60	243 43	1.07	5 64	18 41049
53 57	243 75	0.1	1 14	54 6655
53 57	244 84	1 62	7 91	7 368958
59 84	245	0 35	2 39	42 78643

53 57	245	0 35	2 5	42 74713
59 84	245	0 21	1 65	49 12126
54 82	245	0 56	3 55	34 16269
59 84	243 9	1 8	8 17	5 418854
59 53	244 37	0 12	1 14	53 87811
59 84	223 82	0 22	1 59	57 56422
54 82	245	1 62	7 86	7 304274
58 9	245	0 85	4 82	23 99771
58 59	240 76	0 89	4 91	24 27884
53 57	245	0 2	1 67	49 61116
59 84	245	0 1	1 08	54 18497
57 49	245	0 03	0 7	57 67107
58 59	245	0 7	4 14	29 02914
58 59	245	1 45	7.16	9 658441
54 04	239 98	1 08	5 8	19 17461
58 59	245	0 23	1 8	48 01589
56 08	224 92	0 14	1 23	61 20351
59 84	245	0 22	1 72	48 57517
59 84	244 53	1 71	7 92	6 199197
52 31	243 75	0 23	1 88	48 50343
60	245	0 58	3 56	33 28792
57 33	239 35	0 1	1 09	56 63303
58 59	241 71	0 23	1 78	49 39951
58 59	245	0 22	1 73	48 55837
59.84	244 69	1 89	8.43	4 666605
59 84	244 37	1 24	6 34	13 89499

**Table 7.3.6 : NSGA population for process model by 3<sup>3</sup> factorial design on Moldflow Simulator for LDPE Diskcady**

<b>Pareto Optimal Solutions</b>				
<b>Process Variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Temp. Diff</b>	<b>Ac. Inj. Time</b>
<b>°C</b>	<b>°C</b>	<b>Sec</b>	<b>°C</b>	<b>Sec</b>
60	245	1 51	7 3	1 61308
60	244 37	0 01	0 55	0 008064
60	244 84	0 01	0 55	0 007986
60	239.67	0 01	0 54	0 008743
60	239 2	0 06	0.8	0 058917
59 37	245	0 01	0.55	0 007951
60	244 84	0 01	0 55	0 007986
59.69	245	0.01	0 55	0 007955
58 75	245	0.01	0 56	0 007942
60	243 75	0 01	0 55	0 008165
49 96	245	0 01	0 64	0 00782
59 84	239 98	0 01	0 55	0 008701
54 98	244 84	0 01	0 59	0 007916
54 2	234 96	1 51	7 24	1 614455
60	245	0 01	0.55	0 007959
49.33	243 59	0.01	0 64	0 008042
60	244 84	0 01	0 55	0 007986
60	245	0 2	1 59	0 208416
53.1	245	1 51	7 58	1 612696
60	239 98	0 39	2 53	0 409721
56 86	242 49	0 01	0 57	0 008314
60	239 2	0 01	0 54	0 0088
60	245	0.01	0.55	0 007959
59 84	245	0.01	0 55	0 007957
60	239 2	0 76	4 29	0 811063
49 65	245	0 01	0 64	0 007816
60	245	0 01	0 55	0 007959
59 37	245	0 01	0 55	0 007951
59 84	245	0 01	0 55	0 007957
59 84	245	0 01	0 55	0.007957
59.84	245	0 01	0 55	0 007957
60	244 69	0 01	0 55	0 008012
60	245	0 01	0 55	0 007959
49 65	245	0 1	1 19	0 10801

59 84	244 69	0 01	0 55	0 00801
60	245	0 01	0 55	0 007959
59 37	239.35	0 01	0 55	0 008773
60	244 22	0 01	0 55	0 00809
54 35	245	0 01	0 6	0 007881
60	239 98	0 01	0 54	0 008703
44 63	239 98	0 2	1 76	0 208892
59 37	245	0 01	0 55	0 007951
60	245	0.01	0.55	0.007959
39.29	245	0 01	0.73	0.007672
60	245	0.01	0.55	0.007959
59.22	245	0 39	2 59	0 408905
60	242 33	0.01	0 55	0 008381
60	244 37	0 06	0 81	0.058174
58 75	245	0.01	0 56	0 007942
60	243 75	0.01	0 55	0 008165
60	244 69	0 01	0 55	0 008012
59 37	245	0 01	0 55	0 007951
53 73	245	0.01	0 6	0 007872
59 84	244 69	0 01	0 55	0 00801
60	245	0.01	0 55	0.007959
57.49	237 31	0 1	1 08	0 109213
60	244 37	0 03	0 68	0 033119
60	224 61	0 01	0 51	0 009665
58.75	244.84	0 01	0 56	0 007968
59.84	245	0 01	0 55	0.007957
59 84	245	0 01	0 55	0 007957
58.75	244.69	0.01	0 56	0 007995
59.69	245	0.01	0 55	0 007955
58 75	245	0 01	0.56	0 007942
60	234 96	0 01	0 54	0 009236
58 59	245	0 1	1 09	0 108158
59 84	245	0 03	0 68	0 033011
39.92	245	0 01	0 72	0 007681
57.18	244 84	0 01	0 57	0 007947
59.37	245	0 2	1 6	0 208404
59 69	245	0 01	0 55	0 007955
60	245	0 01	0 55	0 007959
59 84	245	0 01	0.55	0 007957
60	243 75	0 01	0.55	0 008165

60	244.69	0.01	0.55	0.008012
58.75	245	0.01	0.56	0.007942
54.67	244.84	0.01	0.6	0.007912
49.96	245	0.01	0.64	0.00782
59.84	243.75	0.01	0.55	0.008163
60	224.14	0.01	0.5	0.009663
54.98	244.69	0.01	0.59	0.007942
60	245	0.01	0.55	0.007959
60	243.75	0.01	0.55	0.008165
60	245	0.01	0.55	0.007959
59.84	245	0.03	0.68	0.033011
59.37	245	0.01	0.55	0.007951
60	245	0.01	0.55	0.007959
60	244.84	0.01	0.55	0.007986
59.84	239.98	0.01	0.55	0.008701
60	243.75	0.01	0.55	0.008165
57.49	245	0.01	0.57	0.007925
59.84	245	0.01	0.55	0.007957
33.02	244.53	0.1	1.35	0.107816
59.84	245	0.01	0.55	0.007957
60	244.37	0.01	0.55	0.008064
60	244.84	0.01	0.55	0.007986
59.84	245	0.01	0.55	0.007957
60	244.84	0.01	0.55	0.007986
39.92	245	0.01	0.72	0.007681
59.84	244.84	0.01	0.55	0.007984

**Table 7.3.7 : NSGA population for process model by CCD rotatable design on Moldflow Simulator for Polystyrene Diskcady**

<b>Pareto-Optimal Solutions after 50 Generations</b>				
<b>Process Variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Inj. Pre.</b>	<b>Temp. Diff.</b>
<b>°C</b>	<b>°C</b>	<b>Sec</b>	<b>MPa</b>	<b>°C</b>
70	224.06	0.37	25.57	0.396703
69.61	225	1.52	10.74	1.627452
70	224.69	0.29	26.84	0.308767
70	225	1.17	13.25	1.251556
70	224.22	0.37	25.47	0.396758
70	224.37	0.3	26.79	0.321252
69.22	224.37	0.37	25.63	0.396945
69.8	224.37	0.25	27.83	0.270901
69.8	225	1.63	10.15	1.740106
70	224.69	1.17	13.44	1.251446
57.06	225	1.59	14.84	1.700359
69.8	219.98	1.63	13.08	1.73834
70	224.22	0.37	25.47	0.396758
70	224.53	1.51	10.92	1.614788
70	224.84	0.12	30.31	0.132399
69.8	224.37	1.51	11.11	1.614724
69.61	224.37	1.45	11.54	1.552109
69.61	214.8	1.91	15.15	2.036594
70	224.06	0.37	25.57	0.396703
41.57	219.04	0.77	26.74	0.820921
70	224.69	0.3	26.6	0.321363
69.8	223.9	0.2	29.38	0.207735
70	225	1.7	9.81	1.815186
44.9	224.84	0.12	33.91	0.132607
69.8	223.9	0.95	16.48	1.01276
69.8	224.37	0.2	29.09	0.2079
70	224.37	0.2	29.03	0.20786
69.8	224.69	0.37	25.25	0.396957
69.8	224.37	1.45	11.45	1.552115
70	222.49	0.81	19.13	0.861527
69.8	225	1.63	10.15	1.740106
70	223.27	0.01	34	0.00574
70	224.37	0.2	29.03	0.20786
69.8	224.22	0.14	30.49	0.144827

69 8	224 53	0 02	33 03	0 018844
70	224 37	1 45	11 37	1 552122
69 02	222 96	0 95	17.33	1 012489
69 8	223 9	0 2	29 38	0 207735
63 53	225	1 63	12 67	1 739311
69 61	225	1 45	11 15	1 552327
57 45	224 53	0 21	31 6	0 221774
70	225	0.3	26 41	0 321474
70	224 37	0 3	26 79	0 321252
69 8	225	1 63	10 15	1 740106
69 8	224.37	1 45	11 45	1 552115
70	224 69	0 68	19 77	0 724053
69 8	204 29	1 63	19 95	1 732715
70	224 37	1.51	11 02	1 614732
70	224.37	0.37	25 38	0 396814
70	223 27	0 01	34	0 00574
68 24	223 9	0 76	19 6	0 811929
69 8	224.37	1 44	11 53	1 539591
68 43	224 53	0.01	33 7	0 006541
70	224 22	0 25	27 87	0 270807
69 8	224 22	0 76	18 86	0 811895
69.8	224 22	0 02	33 22	0 018734
70	224 06	0 37	25 57	0.396703
70	224.06	1 17	13 82	1 251224
69 8	224.84	0 3	26 57	0 321453
70	224 37	0.25	27 77	0.270863
69.8	225	1 87	9 52	2 002709
69 8	224 37	0.12	30 66	0 132276
70	224 69	0 37	25 19	0 396924
69 8	225	1 63	10 15	1 740106
70	224.84	1.74	9 76	1.865159
69 61	224 22	0 37	25.6	0 396826
70	224 69	1 15	13 68	1.226361
70	224.06	0 01	33 54	0 006017
70	224.53	0.02	32 97	0 018797
69 8	224.37	1 25	12 95	1 339109
69 61	224 37	0 37	25 51	0 396881
69 41	224 37	0 37	25 57	0 396913
69 41	225	1 59	10 48	1 702537
69 61	225	1 15	13 64	1 226478

69 41	225	1 15	13.72	1 22648
69 8	224 37	0 25	27.83	0 270901
63 73	224 37	1 51	13 48	1 614152
70	224.69	0 37	25.19	0 396924
69 8	224 37	1 45	11 45	1 552115
70	204 61	0 3	36 05	0.314142
63 33	225	1 63	12 74	1 739276
69 8	224.37	1 51	11 11	1 614724
70	224 22	0 57	21 8	0 610706
69.8	225	0 79	17 87	0 849867
69 8	224 22	1.65	10 54	1.764855
70	224 53	0.02	32 97	0 018797
70	224.37	0 3	26.79	0 321252
70	224 37	0 37	25 38	0 396814
70	219.67	0.01	36 04	0 004458
70	224 69	0 37	25 19	0 396924
66 47	225	1 45	12 41	1 552104
69 8	224 37	0 22	28 58	0 233103
69 8	224.22	0.24	28.18	0 258247
68.24	222 18	1	17 37	1.075028
69.61	225	1.51	10 81	1.614933
70	224.69	0 02	32 87	0 018853
70	225	0 3	26 41	0 321474
69.8	224.37	1 45	11 45	1 552115
69 61	225	1.59	10.39	1 702551
70	224.06	0.37	25.57	0.396703

**Table 7.3.8 : NSGA population for process model by CCD rotatable design on Moldflow Simulator for Polystyrene Diskcady**

<b>Pareto Optimal Solutions after 50 Generations</b>				
<b>Process Variables</b>			<b>Responses</b>	
<b>Mold Temp.</b>	<b>Melt Temp.</b>	<b>Inj. Time</b>	<b>Temp. Diff.</b>	<b>Inj. Pre.</b>
<b>°C</b>	<b>°C</b>	<b>Sec</b>	<b>°C</b>	<b>MPa</b>
70	224.84	0.91	4.25	16.28481
70	224.84	1.8	6.7	9.629505
70	225	0.01	0.92	32.96558
70	214.65	0.02	0.88	38.29068
70	224.22	0.86	4.08	17.28967
70	224.84	1.29	5.39	12.28337
70	224.84	0.3	2.09	26.5074
70	224.84	0.3	2.09	26.5074
70	224.22	0.91	4.24	16.6669
70	224.84	0.3	2.09	26.5074
57.45	225	0.03	1.35	35.11712
70	219.82	1.1	4.68	16.97155
70	224.22	0.86	4.08	17.28967
70	224.84	1.85	6.8	9.551772
70	224.22	0.01	0.91	33.44254
70	224.84	0.02	0.97	32.77904
70	224.84	0.3	2.09	26.5074
70	224.84	0.29	2.05	26.74913
70	224.84	0.01	0.92	33.06165
69.8	224.22	1.43	5.76	11.69858
70	224.84	0.91	4.25	16.28481
69.8	225	0.03	1.02	32.46019
69.22	224.84	0.3	2.12	26.7564
70	224.84	0.01	0.92	33.06165
70	224.84	0.86	4.1	16.90764
70	224.84	0.11	1.35	30.57948
70	224.84	0.11	1.35	30.57948
70	224.84	0.1	1.3	30.84846
70	224.84	0.3	2.09	26.5074
70	224.84	0.3	2.09	26.5074
70	224.84	0.35	2.27	25.55752
70	224.84	0.07	1.16	31.66563
70	224.84	0.11	1.35	30.57948
70	224.84	0.11	1.35	30.57948

70	224 22	0 01	0 91	33 44254
70	224 22	0 91	4 24	16 6669
69 22	224 84	1 1	4 87	14 37241
68.43	224.22	0.01	0.95	33 89055
63 73	224 84	0 35	2.47	27 35293
69 8	224 22	1 05	4 68	15 03866
57 45	224 22	0 2	2 04	32 03118
70	224 84	0 16	1 54	29 52058
70	224 84	1 29	5 39	12 28337
70	224 84	1 29	5 39	12 28337
70	224 84	0 11	1.35	30 57948
70	224 84	1.29	5 39	12 28337
70	224 84	0 91	4 25	16 28481
70	224 84	0.07	1.16	31 66563
70	224.84	0 35	2.27	25.55752
70	224.84	0.3	2.09	26.5074
70	224.53	0.3	2.09	26 69873
70	224 84	0 11	1 35	30 57948
43.33	219 82	0 28	2 7	33 84222
66.86	214 8	0.04	1 05	38 53665
70	224 84	0 11	1.35	30 57948
70	224 84	0 11	1 35	30 57948
70	224 22	0 16	1 53	29 90167
70	224 84	0 02	0.97	32 77904
69.8	225	0 3	2.1	26 47422
70	219.82	0 02	0.92	35.67305
69.61	224 84	0 11	1 36	30 69823
70	224 84	0 35	2.27	25 55752
70	224 84	0.16	1 54	29 52058
70	224.84	0 35	2 27	25 55752
70	224 84	2 46	7 96	11 02142
69.8	224 22	0.86	4.09	17 36281
70	224.84	0 14	1 45	30 04662
70	214.8	0.3	1.95	31.95119
70	224.84	0.35	2 27	25 55752
70	224 84	0 3	2 09	26 5074
70	224.84	0.91	4.25	16 28481
70	224 84	0 16	1.54	29 52058
69 8	214 96	0 3	1 96	31 94025
70	224 22	1 05	4 68	14 96214

70	225	0 3	2 1	26 41123
70	224 84	0.3	2.09	26 5074
63 73	224 84	0 3	2.29	28 27582
70	224 84	0 16	1 54	29 52058
70	224 84	0 11	1 35	30 57948
70	204.76	0 35	1 99	35 04617
63 73	224 22	0 01	1.08	35 04296
70	223.59	0.35	2 25	26.31474
70	224 84	0 16	1.54	29.52058
70	224 84	0.29	2 05	26.74913
70	224 84	0.01	0 92	33 06165
70	224 84	0 11	1 35	30 57948
70	204.76	1.8	5.84	19 18009
70	225	0.01	0.92	32.96558
70	219 82	0.3	2 02	29 40441
70	224.84	0.3	2.09	26 5074
66.86	225	0 02	1 05	33 54998
70	224.84	0.1	1 3	30.84846
70	224.53	0.3	2.09	26 69873
70	223.59	0 1	1 29	31.60502
70	224.84	0 1	1 3	30 84846
70	225	0.02	0 97	32 68296
70	224.84	0.3	2 09	26 5074
70	224.84	0.3	2 09	26 5074
70	224.84	0.35	2 27	25 55752
70	224.84	0.91	4 25	16 28481

**Table 7.3.9: NSGA population for process model by Box - Behenkin design on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions after 50 Generations</b>					
<b>Process Variables</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>Fill Time</b>	<b>Cooling Time</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>Sec</b>	<b>Sec</b>
201.88	35	298.04	10000	0.000932	2.162
224.78	35	298.04	10000	0.000916	2.44
211.92	35	294.12	10000	0.000923	2.289
206.9	35	298.04	10000	0.000927	2.226
217.57	35	294.12	10000	0.000918	2.357
224.47	35	294.12	10000	0.000914	2.437
206.9	35	298.04	10000	0.000927	2.226
206.9	35	298.04	10000	0.000927	2.226
208.16	35.18	296.08	10000	0.000926	2.243
206.9	35	298.04	10000	0.000927	2.226
208.16	35	298.04	10000	0.000925	2.242
211.92	40.65	297.06	10000	0.000926	2.351
208.16	35	294.12	10000	0.000926	2.242
217.57	35	172.55	10000	0.001265	2.359
216.94	35	294.12	10000	0.000919	2.349
211.92	35	298.04	10000	0.000922	2.289
206.9	35	298.04	10000	0.000927	2.226
208.16	35	282.35	10000	0.000933	2.242
220.71	35	298.04	10000	0.000917	2.393
213.18	35	298.04	10000	0.000921	2.304
201.88	35	298.04	10000	0.000932	2.162
216.94	35	294.12	10000	0.000919	2.349
200.94	35	298.04	10000	0.000933	2.15
206.9	35	298.04	10000	0.000927	2.226
201.88	35	235.29	10000	0.001043	2.162
201.88	35	298.04	10000	0.000932	2.162
211.92	35	298.04	10000	0.000922	2.289
205.65	35	298.04	10000	0.000928	2.21
220.71	35	298.04	10000	0.000917	2.393
201.88	35	298.04	8807.84	0.001028	2.163
228.24	35	297.06	10000	0.000914	2.479
204.39	35	298.04	10000	0.000929	2.194
211.92	35	298.04	10000	0.000922	2.289
201.88	35	290.2	10000	0.000936	2.162

201 88	35	298.04	9701.96	0.000941	2 162
221 96	35	298 04	8807 84	0 001006	2 408
225.73	36 41	298 04	10000	0 000916	2 459
224 47	35	298 04	10000	0.000916	2 437
210.67	35	290 2	10000	0 000925	2 273
213 18	35	298 04	10000	0 000921	2 304
206.9	35	282.35	10000	0 000935	2 226
201 88	35	298.04	10000	0 000932	2 162
208.16	35.18	294.12	9701 96	0 000936	2 243
200 63	35	290 2	10000	0 000938	2 146
201 88	35	298 04	10000	0 000932	2 162
205.65	35	250.98	10000	0.000988	2 21
201.88	35	298.04	10000	0.000932	2 162
208 16	35	297.06	10000	0.000926	2 242
224.78	35	298.04	10000	0.000916	2 44
206 9	35	298.04	10000	0.000927	2 226
201 88	35	298.04	10000	0 000932	2 162
206.9	35	298.04	10000	0 000927	2 226
225 73	35	298.04	9701.96	0 000923	2.451
208 16	35	298.04	10000	0.000925	2 242
217.57	35	298.04	10000	0.000918	2.357
204.71	35	298.04	10000	0.000929	2 198
206.9	35	298.04	9701.96	0.000935	2.226
211.92	35	298.04	10000	0.000922	2.289
206.9	35.18	298.04	10000	0.000927	2 227
206 9	35	298 04	10000	0.000927	2 226
208.16	35	298 04	10000	0.000925	2 242
201 88	35	297.06	10000	0.000932	2.162
206.9	35	298 04	10000	0 000927	2 226
208.16	35	297.06	10000	0 000926	2 242
217.57	35	294.12	10000	0 000918	2 357
209 1	35	294.12	10000	0.000925	2 254
206.9	35	298.04	10000	0 000927	2 226
211.92	35	294.12	10000	0 000923	2 289
208.16	35	298.04	10000	0.000925	2.242
205.65	35	298.04	10000	0 000928	2 21
206.9	57.59	297.06	10000	0.000937	2 993
201 88	35	298 04	10000	0.000932	2 162
220.71	35	298 04	10000	0 000917	2 393
211.92	35	294.12	10000	0.000923	2 289

208.16	35	298 04	10000	0.000925	2 242
206 9	35	298.04	10000	0.000927	2 226
206 9	35	294 12	10000	0 000928	2 226
217 57	35	298 04	8807 84	0 00101	2 357
225 73	35	298 04	10000	0 000915	2 451
208 16	35	298 04	10000	0 000925	2 242
204 39	35	298.04	10000	0 000929	2 194
208 16	35	298.04	10000	0 000925	2 242
208 16	35	294 12	10000	0 000926	2 242
217 57	35	298 04	10000	0 000918	2 357
206 9	35	298.04	10000	0 000927	2 226
201 88	35	298.04	10000	0 000932	2 162
208 16	35	298 04	10000	0 000925	2 242
206.9	35	298.04	10000	0.000927	2 226
206.9	40.65	294.12	10000	0 000931	2 288
208.16	35	298 04	10000	0 000925	2 242
208 16	35	298.04	10000	0.000925	2 242
224 78	35	298.04	10000	0.000916	2 44
208.16	35	297.06	10000	0 000926	2 242
206.9	35	298 04	10000	0.000927	2.226
224.78	35	298 04	9701.96	0.000923	2 44
206 9	35	294.12	10000	0 000928	2 226
206.9	35	298.04	10000	0.000927	2 226
206.9	35	298.04	10000	0.000927	2 226
200 63	35	298.04	10000	0 000934	2.146
201 88	35	298.04	10000	0.000932	2 162

**Table 7.3.10: NSGA population for process model by Box - Behenkin design on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions after 50 Generations</b>					
<b>Process Variables</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>In.j Pre.</b>	<b>Fill Time</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>MPa</b>	<b>Sec</b>
280	79.47	178.43	9441 18	72.987	0 001097
280	79 12	245 1	9552 94	77 321	0 000948
280	79 82	82 35	9813 73	61 609	0 001622
280	79 12	245.1	9515.69	77 25	0 000951
279 69	76 47	162 75	9552 94	71 853	0 001151
279 69	79 82	50 98	7466 67	53 669	0 00246
280	79.12	206 86	9888 24	75 881	0 000983
280	77 88	55 88	9813 73	57 159	0 001852
280	79 82	182 35	9552 94	73 484	0 001072
280	79 82	144 12	9888 24	70 143	0 001211
280	75 94	114 71	9552 94	66.19	0 001414
280	74.18	144 12	9888 24	70.273	0 001212
280	76 47	162 75	9552.94	71 777	0 00115
279 69	79 12	216 67	4784 31	62 974	0 002595
280	79 29	90 2	9441.18	62 498	0 001603
280	73 47	58 82	9925 49	57 83	0.001816
280	79.12	206 86	9925.49	75 938	0.000981
280	79.29	105 88	9888 24	65 241	0 00144
280	79 47	178 43	9441.18	72 987	0 001097
280	79 12	245 1	9925 49	78 004	0.000933
280	79 82	144 12	9552.94	69 731	0 001238
280	77 88	71 57	9925 49	59 962	0 001702
280	79 12	148.04	9925 49	70 646	0 001189
280	80	90 2	9441 18	62 484	0 001603
280	79 29	152 94	9925.49	71 181	0 001165
280	77 71	194 12	9552 94	74 479	0 001035
280	79 12	208 82	9776 47	75 837	0 000983
279 69	79 12	245 1	9515 69	77 344	0 00095
280	79 82	58 82	9888 24	57 697	0 001817
280	79 12	175 49	9552 94	72.909	0 001097
280	79 29	50	8360 78	54 727	0 002182
279 37	79 12	175 49	9776 47	73 387	0 001081
280	77 71	194 12	9552 94	74 479	0 001035
280	79 29	86 27	9739 22	62 176	0 001599

279 69	77 88	146 08	9552 94	70 067	0 00123
280	79 12	55 88	8360 78	55 745	0 002124
280	75 94	114 71	9515.69	66 148	0 001418
280	77 88	71 57	9925 49	59 962	0 001702
269 96	78 76	178 43	9925 49	76 305	0 001079
280	79 12	245 1	9441 18	77 105	0 000956
280	74 18	193 14	9105 88	73 74	0 001087
280	77 88	146 08	10000	70 54	0 001195
280	79 82	118 63	9552 94	66 628	0 001387
279 69	79 82	50 98	7466 67	53.669	0 00246
280	79 12	208 82	9776 47	75 837	0 000983
280	80	115 69	9552 94	66 235	0 001406
280	79 82	144 12	9552 94	69 731	0 001238
280	80	90.2	9515 69	62 559	0 001593
279 06	79 12	55 88	9925 49	57 36	0.001845
280	79 82	144.12	8360.78	67 885	0 001438
280	79 82	58.82	9925.49	57 721	0 001813
279 69	79 82	58 82	7466 67	54 97	0 00238
277 49	79 12	245 1	9627 45	78 22	0 000943
280	80	147 06	9515 69	70 004	0 001227
280	79 12	245 1	9552 94	77 321	0 000948
280	80	147 06	9515 69	70.004	0 001227
280	79 82	118 63	9590 2	66 67	0 001383
280	79.29	94 12	9739 22	63 379	0 001538
280	76.47	208 82	10000	76.257	0 000975
279 69	76 29	208 82	10000	76 348	0.000975
280	79.29	90 2	9925.49	62.942	0.001551
280	79 29	50	8360 78	54 727	0.002182
280	77 88	55.88	8994.12	56 482	0 001977
280	79 12	224 51	9813 73	76 841	0 000954
279 69	79 82	182.35	9515 69	73 507	0 001076
279 69	76 47	162.75	9552 94	71 853	0 001151
277.49	79 29	62 75	9739.22	58 716	0 00181
280	73 47	206 86	9478.43	75 368	0.001009
280	79 12	206 86	9552.94	75 341	0 001002
277 18	79 12	55 88	9552 94	57.415	0.001898
280	79 82	58 82	9888 24	57.697	0 001817
269 96	79 12	208 82	9552 94	78 292	0.001007
280	75 94	114 71	9552.94	66.19	0 001414
280	79 82	144 12	9552 94	69 731	0 001238

280	73.65	62 75	10000	58 567	0 001774
280	76 29	208 82	9739 22	75 856	0 000986
280	80	90 2	9515 69	62 559	0 001593
280	79 82	118 63	8696 08	65.494	0 001523
280	79 12	208 82	9776 47	75 837	0 000983
280	79 12	191.18	9515 69	74 157	0 001047
269 96	77 88	146 08	9925 49	72 816	0 001227
280	79 12	245 1	9552 94	77 321	0 000948
280	80	146 08	4784 31	58 924	0 002971
280	79 12	92 16	9515 69	62 873	0 001579
279 69	74 18	177 45	10000	73 916	0 001063
280	79 82	177 45	9105 88	72 351	0 00114
279 69	74 18	177 45	8994 12	72 38	0 001158
278 75	80	177.45	10000	74 002	0 001063
279 69	74 18	293 14	9552 94	78 545	0 000977
280	79 12	91 18	4784 31	53 327	0 003427
280	79 12	55 88	9552 94	56 953	0 001883
279.69	79 29	90.2	9925 49	63 001	0 001553
239.53	79.29	150.98	9925 49	81 585	0 001305
279 69	79 82	58 82	9515.69	57 481	0.001862
280	75 94	113 73	9515.69	66.016	0 001425
280	79 82	83 33	9515 69	61.502	0 001648
280	79 12	208 82	9850 98	75 955	0 00098
279 69	79 82	58 82	9776 47	57.675	0 00183
280	79 12	191 18	9515.69	74.157	0.001047
280	79 12	177 45	9441 18	72.912	0 001101

**Table 7.3.11: NSGA population for process model by Box - Behenkin design on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions after 50 Generations</b>					
<b>Process Variables</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>Temp . Diff.</b>	<b>Fill Time</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>°C</b>	<b>Sec</b>
256 16	35	270 59	10000	0 115	0 000908
256.16	35	270 59	10000	0 115	0 000908
256 16	37 82	274 51	10000	0 127	0 00091
257 41	35 18	270 59	10000	0 114	0 000908
257 1	35	270 59	10000	0.114	0 000908
257 1	35	270.59	10000	0.114	0 000908
259 92	35	270 59	10000	0 111	0 000909
257 1	35	270 59	10000	0 114	0 000908
259 92	35	270 59	10000	0 111	0 000909
257 1	35	270 59	10000	0 114	0 000908
259 92	35	270 59	10000	0 111	0 000909
259 92	40 65	270 59	10000	0 132	0 000912
259 92	35	270 59	10000	0 111	0 000909
257 1	35	145 1	10000	0 18	0 001268
259 61	35	270 59	10000	0.111	0 000909
257 1	35	270 59	10000	0 114	0 000908
256 16	35	270 59	10000	0 115	0 000908
257 1	35	286 27	10000	0 117	0 000915
257 1	35	270 59	10000	0 114	0 000908
259 61	35	270 59	10000	0 111	0 000909
257.1	35	270 59	10000	0 114	0 000908
257.41	35	270 59	10000	0.113	0 000908
256 16	35	270 59	10000	0 115	0 000908
257.1	35	270 59	10000	0 114	0 000908
257.41	35	207 84	10000	0 126	0 000995
257 1	35	270 59	10000	0 114	0.000908
256.16	35	270.59	10000	0 115	0 000908
259 92	35	270 59	10000	0.111	0 000909
256 16	35	270 59	10000	0 115	0 000908
259 92	35	270 59	10000	0 111	0 000909
259 92	35	270 59	10000	0 111	0 000909
256 16	35	270 59	10000	0 115	0 000908
257 1	36 41	270 59	10000	0 12	0 000909
257 1	35	278 43	10000	0 115	0 00091

256 16	35	270 59	10000	0 115	0 000908
257 41	35	270 59	8807 84	0 141	0 000999
257 41	35	270 59	10000	0 113	0 000908
259 92	35	270 59	10000	0 111	0 000909
247 06	35	270 59	10000	0 133	0 000908
257 41	35	270 59	10000	0 113	0 000908
257 1	35	286 27	10000	0 117	0 000915
257 41	35	270 59	10000	0 113	0 000908
257 1	35	270 59	10000	0.114	0 000908
257 1	35	270 59	10000	0 114	0 000908
257 41	35	270 59	10000	0 113	0 000908
259 61	35	239 22	10000	0.11	0 000927
257 1	35	270 59	10000	0 114	0 000908
259 92	35	274 51	10000	0 111	0 00091
259.92	35	270 59	10000	0 111	0 000909
259 92	35	270 59	10000	0 111	0 000909
257 41	35 18	270 59	10000	0 114	0.000908
257.41	35	270.59	10000	0 113	0.000908
259 92	35	270 59	9701 96	0 115	0.000916
259 61	35	270 59	10000	0 111	0 000909
259.92	35	270.59	10000	0 111	0.000909
259 92	35	270 59	10000	0.111	0 000909
259 92	35	270 59	10000	0 111	0.000909
257 1	35	270.59	10000	0 114	0 000908
256 16	35 18	270 59	10000	0 116	0 000908
257 1	35	270 59	10000	0 114	0 000908
259 92	35	270 59	10000	0 111	0 000909
256.16	35	270 59	10000	0 115	0 000908
258 98	35	270 59	5231 37	0 373	0 002217
259.92	35	270 59	10000	0 111	0 000909
259 92	35	270 59	10000	0 111	0 000909
259.61	35	270 59	10000	0 111	0 000909
259.92	35	270 59	10000	0 111	0 000909
257 1	35	270.59	10000	0 114	0 000908
259 92	35	270 59	10000	0 111	0 000909
259 92	35	270 59	10000	0 111	0 000909
256 16	35	270 59	10000	0 115	0 000908
256 16	35	270 59	10000	0 115	0 000908
257 41	35	270 59	10000	0.113	0 000908
259 92	35	274 51	10000	0 111	0 00091

259 61	35 18	270 59	10000	0 112	0 000909
259 92	35	270 59	10000	0 111	0 000909
255 84	35	270 59	10000	0 116	0 000908
257 41	35	270.59	8807.84	0 141	0 000999
259 92	35	270 59	10000	0.111	0 000909
257 1	35	270 59	10000	0.114	0 000908
249 88	35	270 59	10000	0 127	0 000908
259 92	35	270 59	10000	0 111	0.000909
257 1	35	270 59	10000	0.114	0 000908
259 92	35	270 59	10000	0.111	0.000909
258 98	35	272 55	10000	0.112	0.000909
257 41	35	270 59	10000	0 113	0 000908
257 1	35	270 59	8807 84	0.141	0 000999
256.16	35	270 59	10000	0 115	0 000908
259 92	40 65	270.59	10000	0 132	0 000912
259 92	35	270 59	10000	0 111	0 000909
259 92	35	270 59	10000	0.111	0.000909
256 16	35	270 59	10000	0 115	0 000908
259 92	35	270 59	10000	0.111	0 000909
257 41	35	270.59	10000	0 113	0 000908
256 16	35	270.59	9701 96	0.12	0 000916
256.16	35	270.59	10000	0 115	0 000908
257 1	35	270 59	10000	0.114	0 000908
259 92	35	270 59	10000	0 111	0 000909
257 1	35	270.59	10000	0 114	0 000908
256 16	35	270.59	10000	0 115	0 000908

**Table 7.3.12: NSGA population for process model by Box - Behenkin design  
on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions after 50 Generations</b>					
<b>Process Variables</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>Inj. Pre.</b>	<b>Cooling Time</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>MPa</b>	<b>Sec</b>
200	35 529	51 961	574 51	52 325	2 191
200 627	35 529	50	537 255	51 6	2 2
200	35 529	50	574 51	51 956	2 191
200	35 529	50	574.51	51 956	2 191
215 059	35 529	52 941	574.51	48.068	2 377
200	35 529	51 961	574 51	52.325	2 191
255 216	35 529	50	537 255	37 371	2 794
215 059	35 529	50	574 51	47 548	2 377
201 882	35 529	51 961	574 51	51 752	2 215
200	35 353	51 961	574 51	52 327	2 191
255 843	35 529	51 961	574 51	37 691	2 799
200	41 176	50	537 255	51 71	2 257
215 059	35 529	52 941	574 51	48.068	2 377
215.059	35.529	175.49	537 255	63 861	2.36
215 059	35 529	51 961	574 51	47 896	2 377
245 176	35 529	50	574 51	39.803	2.7
215 686	35 529	51.961	500	47.386	2 385
240 157	35.529	67.647	574.51	43.697	2 648
200	35.529	51 961	574.51	52 325	2 191
200	35.529	50	574 51	51 956	2.191
200	35 529	50	574 51	51 956	2 191
215 059	35.529	51 961	574 51	47.896	2 377
205.02	35.529	52.941	574 51	50 989	2 255
215 059	35 529	50	537 255	47 383	2 377
200	35 529	112 745	574 51	62 355	2 182
245 804	35 529	50	537 255	39 49	2 707
215 059	35 529	50	723 529	48 204	2 376
215 059	35 529	55 882	872 549	49 896	2 374
205 647	35 529	50	574 51	50 261	2 263
240 157	35 529	50	574 51	40.995	2 651
215 059	35 529	51 961	574 51	47 896	2 377
240 784	35 529	52 941	574 51	41 309	2 657
200 627	36 235	50	574 51	51 755	2 203
275 922	35 529	59 804	574 51	34 641	2 963

200	35 529	50	723 529	52.609	2 191
255 216	35 529	51 961	1766.667	42.897	2.788
200	36 235	50	574 51	51 946	2 195
275 922	35 529	50	574 51	33 367	2 965
205 02	35 529	51.961	574 51	50 809	2 255
255 843	35 529	50	574 51	37 402	2 8
252 078	35 529	67 647	574 51	40 778	2 763
258 353	35 529	51.961	574 51	37 149	2 822
210 039	35 529	51 961	574 51	49.332	2 317
205 02	35 529	51 961	574 51	50 809	2 255
200	35 529	51 961	537 255	52 159	2 191
215 059	35.529	84 314	611 765	53.392	2 372
200	35 529	50	574 51	51 956	2 191
200	35.529	50	1803 922	57.065	2 184
255 216	35 529	51 961	574 51	37 828	2 794
200	35 353	51 961	574 51	52 327	2 191
251 451	41 176	50	723 529	39 011	2 828
215 059	35.529	50	574 51	47 548	2 377
217 569	35 529	50	872 549	48 152	2.405
205 02	35 529	181 373	872 549	69 941	2 236
200 627	35 529	50	537 255	51.6	2 2
200	35 529	50	1133 333	54 357	2 188
240 784	35.529	50	872 549	42 157	2 656
205 02	35 529	50	574 51	50 447	2.255
255.216	35.353	55 882	574.51	38 4	2.792
242 039	35 529	51 961	574.51	40 852	2.669
240 157	35 529	52.941	574 51	41.461	2 65
240 157	35 529	51 961	574 51	41 307	2 651
215.059	35 529	50	537 255	47 383	2 377
255 216	35 529	50	574 51	37 538	2 794
200	35 529	50	574 51	51 956	2 191
200 314	35 529	52 941	574 51	52 412	2 195
242 039	35 529	50	574 51	40 543	2 67
200	35 529	51 961	835 294	53 465	2 189
215 059	35 529	50	574 51	47 548	2 377
200 627	38 353	51 961	537 255	51 929	2 221
215 059	35 529	52 941	1803 922	53 225	2 369
215 059	35 529	50	537 255	47 383	2 377
200 627	35 529	50	1133 333	54 166	2 196
200	35 353	51 961	5343 137	68 657	2 165

200 627	35 353	51 961	5343 137	68 47	2 173
200	36 941	51 961	574 51	52 305	2 199
242 667	35 529	53 922	574 51	41 007	2 675
240 157	35 529	52 941	1766 667	46.512	2 644
245 176	35 529	51 961	537.255	39 94	2 7
210 039	35 529	50	574.51	48 978	2 317
245 176	35 529	50	574.51	39 803	2 7
205 02	35 529	50	723 529	51 101	2 254
205 647	35 529	50	537 255	50 096	2 263
215 059	35.529	52 941	574 51	48 068	2 377
215 059	35 529	51 961	574 51	47 896	2 377
215 059	35.529	50	723 529	48 204	2 376
215 059	35 529	51 961	574 51	47 896	2 377
200	35 529	50	574 51	51 956	2 191
200 627	41	51.961	5343 137	68 373	2 236
200	35 529	175.49	574 51	69 842	2 175
240.157	35 529	50	537 255	40 828	2 651
240 157	35 529	51 961	500	40 971	2 651
255.843	35.529	175 49	574 51	50.173	2 782
242 039	35 529	51 961	537 255	40 685	2 67
255 216	35.529	51 961	5641 176	55 247	2 775
200 627	35 353	50	574 51	51 767	2 199
255 216	35 529	52 941	574 51	37 972	2 794
215 059	35 529	50	537.255	47 383	2 377
240.157	35 529	50	574 51	40 995	2 651
255.216	35 529	51 961	574 51	37 828	2 794

**Table 7.3.13: NSGA population for process model by Box - Behenkin design on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions 50 Generations</b>					
<b>Process Variable</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>Tem p Diff.</b>	<b>Cooling Time</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>°C</b>	<b>Sec</b>
243.92	35	268.63	10000	0.142	2.645
246.43	35	268.63	10000	0.135	2.67
216.31	35	268.63	10000	0.268	2.342
251.76	35	268.63	10000	0.123	2.721
256.47	35	268.63	10000	0.115	2.765
257.1	35	268.63	10000	0.114	2.771
259.61	35	268.63	10000	0.111	2.793
216.31	35	268.63	10000	0.268	2.342
261.49	35	268.63	10000	0.109	2.81
261.49	35	268.63	10000	0.109	2.81
256.47	35.18	268.63	10000	0.115	2.766
216.63	40.65	267.65	10000	0.289	2.408
243.92	35	268.63	10000	0.142	2.645
261.49	35	143.14	10000	0.162	2.814
256.47	35	268.63	10000	0.115	2.765
241.73	35	268.63	10000	0.149	2.623
256.47	35	268.63	10000	0.115	2.765
253.96	35	252.94	10000	0.12	2.742
243.92	35	268.63	10000	0.142	2.645
241.41	35	268.63	10000	0.15	2.619
244.55	35	268.63	10000	0.14	2.651
256.47	35	268.63	9962.75	0.115	2.765
256.47	35	264.71	10000	0.114	2.765
216.31	35	268.63	10000	0.268	2.342
243.92	35	205.88	10000	0.179	2.646
248	35	258.82	10000	0.133	2.685
216.63	35	268.63	9701.96	0.277	2.346
244.24	35	268.63	10000	0.141	2.648
248	35	268.63	10000	0.131	2.685
261.49	35	268.63	10000	0.109	2.81
248	35	268.63	8807.84	0.165	2.685
241.73	35	268.63	10000	0.149	2.623
241.73	35	259.8	10000	0.152	2.623
245.49	35	260.78	10000	0.14	2.66

256 47	35 18	268 63	10000	0 115	2 766
216 31	35	268 63	10000	0 268	2 342
206 27	35	268 63	10000	0 336	2 218
261 8	35	268 63	8807 84	0 133	2 812
246 43	35	268.63	10000	0 135	2 67
253 96	35	268 63	10000	0 119	2 742
246 43	35	268 63	10000	0 135	2 67
256 47	35	268.63	10000	0 115	2 765
246 75	35	268.63	10000	0 134	2.673
243 92	35	263 73	10000	0 144	2 645
241 73	35	268 63	10000	0 149	2 623
241 73	35	268 63	10000	0 149	2 623
253 96	35	268 63	10000	0 119	2 742
251 45	35	268 63	10000	0 123	2 718
216 63	40 65	268 63	10000	0 288	2.408
266 82	35	268 63	10000	0 106	2 856
253 96	35	268 63	10000	0 119	2 742
256 47	35	268 63	10000	0 115	2 765
246 43	35	264 71	10000	0 136	2 67
256 47	35	267 65	10000	0 114	2 765
246 43	35	268 63	9701 96	0 141	2.67
251 45	35	268 63	10000	0 123	2 718
256 47	35	268 63	10000	0 115	2 765
264 63	35	268 63	10000	0 107	2 837
246 43	35	268 63	10000	0 135	2 67
203 76	35	268 63	10000	0 355	2 186

**Table 7.3.14: NSGA population for process model by Box - Behenkin design on CMOLD simulator for polypropylene Tape casing**

<b>Pareto Optimal Solutions 50 Generations</b>					
<b>Process Variables</b>				<b>Responses</b>	
<b>Melt Temp.</b>	<b>Mold Temp.</b>	<b>M. Inj. Pre.</b>	<b>M. Inj. Rate</b>	<b>Inj. Pre.</b>	<b>Temp Diff.</b>
<b>°C</b>	<b>°C</b>	<b>MPa</b>	<b>Cm3/sec</b>	<b>MPa</b>	<b>°C</b>
280	37 12	53 92	6162 75	51 99	0 332573
280	37 12	50	5566 67	49 98	0 383219
280	36 06	50	1990 2	38 61	0 784328
280	37 12	50	5566 67	49 98	0 383219
280	35 71	50	7354 9	53.65	0 262789
274 98	37 12	50	5566 67	50 86	0 42146
280	37 47	50	5566 67	49 98	0 384605
280	35	53 92	7354 9	54 32	0 253933
280	35 88	50	5566 67	49 98	0 378233
280	35 88	50	5566 67	49 98	0 378233
280	37 65	57 84	2623 53	42 11	0 690159
280	42 76	50	5566.67	49.97	0.403297
280	37 47	50	5305.88	49 33	0 406234
280	37 47	175.49	6162 75	66 15	0 23046
280	36 76	50	5566 67	49 98	0 381816
280	37 12	50	5566 67	49 98	0 383219
280	37 47	50	7354 9	53 64	0 269891
280	36 41	69 61	5566 67	52 99	0 352529
280	37 12	53 92	6162 75	51 99	0 332573
280	37 12	50	5566 67	49 98	0 383219
280	35 71	53 92	6162 75	51 99	0 326856
280	36.76	50	5566 67	49 98	0 381816
280	36 24	51 96	9739 22	56 81	0 200276
277.49	39.94	53 92	7354 9	54 74	0 28916
280	36 41	116 67	7354 9	63 45	0 187216
280	37 47	50	7354.9	53 64	0 269891
280	36 06	50	5566 67	49 98	0 378958
280	37 47	50	9143 14	55 97	0 213825
280	35.71	50	6162 75	51 35	0 332749
280	36 76	50	5566 67	49 98	0 381816
280	37 12	53 92	7354 9	54 31	0 262613
280	37 47	50	5566.67	49 98	0 384605
280	37 47	57 84	7950 98	55 92	0 23306
280	37 47	57 84	5566 67	51 22	0 37298

280	37 47	50	7354 9	53 64	0 269891
280	36 06	50	5566 67	49 98	0 378958
280	37 47	50	6758 82	52 57	0 301613
280	36 41	53 92	7354 9	54 31	0 259789
269 96	36 41	50	8547 06	57 11	0 284421
279 69	37 12	50	5268 63	49 29	0 410396
280	37 12	65.69	1692 16	39 48	0 810346
280	37.12	50	7354 9	53 65	0 268506
280	37.12	50	5566.67	49 98	0 383219
280	37 12	50	5566 67	49 98	0 383219
280	36 76	50	5566.67	49 98	0 381816
280	36 76	81 37	5566 67	54 66	0 339144
280	36 06	53 92	7354 9	54 31	0 258352
280	37 12	50	5566 67	49 98	0 383219
280	36 76	53 92	6013.73	51 66	0 341747
280	37 47	50	5268 63	49 24	0 409426
280	36 06	50	5566 67	49 98	0 378958
280	37 12	50	8249 02	54 98	0 233142
277 49	37 12	50	7056 86	53 56	0 300199
280	37 47	50	5566.67	49 98	0 384605
280	35 71	53 92	7354 9	54.31	0 256896
280	36 76	50	5641 18	50 16	0 375866
280	35 71	53 92	7056 86	53 79	0 271943
280	37 12	50	5566 67	49 98	0 383219
280	37 29	50	7354 9	53.65	0 269201
280	36.76	50 98	5566 67	50 13	0 380329
280	35 71	50	8249 02	54 98	0 227424
280	36 06	50	6758 82	52 57	0 295966
280	35.88	50	5566 67	49 98	0 378233
280	37 12	50	5566 67	49 98	0 383219
280	35 71	50	5268.63	49.24	0 402324
279 69	37 47	50	9143 14	56 02	0 215497
280	36 41	50	5566 67	49.98	0.380396
280	37 47	50	5566.67	49 98	0.384605
280	37.47	50	5566 67	49 98	0 384605
269.96	37 47	50	6162 75	53 14	0 415936
280	35 71	50	6162.75	51 35	0 332749
280	37 47	50	5566 67	49 98	0 384605
280	36 76	50	5641 18	50 16	0 375866
280	36 06	50	5566 67	49 98	0 378958

280	37 12	50	6013 73	51 02	0 349043
280	37 65	50	5566 67	49 98	0 385292
280	37 47	50	9143 14	55 97	0 213825
280	35 71	53 92	6162 75	51 99	0 326856
239.84	36 76	50	5566 67	58 14	0 770847
280	37 47	50	5566 67	49 98	0 384605
267 45	37 47	50	7354 9	55 89	0 358446
280	37 12	50	5566 67	49 98	0 383219
280	36 06	50	5566 67	49 98	0 378958
280	35 71	53 92	5566 67	50 6	0 37161
280	37 47	53 92	2623 53	41 57	0 695206
280	37 12	50	1692 16	37 42	0 832959
280	37 29	51 96	6460.78	52 3	0 316261
280	37.29	53 92	7354 9	54 31	0 263308
280	41 53	50	5268 63	49.23	0 424107
280	35.88	50	5566.67	49.98	0 378233
280	36 41	50	6758 82	52 57	0 297404
280	36 06	53 92	7354 9	54 31	0 258352
280	37.12	50	5566 67	49 98	0 383219
280	37 12	50	5566 67	49 98	0 383219
280	37 47	50	1692 16	37 42	0 834345
280	36 06	50	6758 82	52 57	0 295966
280	60 24	50	6013 73	50 91	0 40296
269 96	37 12	50	9143 14	57 72	0 27171
280	37 65	57 84	2623 53	42 11	0 690159
280	37.47	53 92	8845 1	56 38	0 213204

confirmed that such solutions may be verified subsequently by comparing the “optimum” given by the model with a subsequent run of the simulator

- 3 Product quality in injection molding is a function of the material used, the mold design, cooling system design and processing conditions. The processing conditions that are important for quality of the injection molded part are mold temperature, melt temperature and fill time. Quantitative measures of the injection molded part quality are developed. These quantitative measures constitute the objective function that must be minimised. The DOE framework can isolate the significant process factors from those that are not.
- 4 Second-order regression models appear to be reasonably good to represent the process models for flow simulation outputs from an injection molding simulation software. However, the models are not perfect and require verification runs before the final results may be accepted.
- 5 Population based “genetic algorithms” is well suited to injection molding process parameter optimisation. Since the GA gives a group of solutions, decision maker may subsequently choose a particular solution depending on his/her requirements and preference.
- 6 *Multiple objective* process optimisation using GA has been done in this work for injection molding. The concept of Pareto-optimality was used to solve the Bi-objective problems using “non-dominated sorting genetic algorithm” (NSGA). To the best of the investigator’s knowledge, this has not been attempted before (see for instance, Kumar A, 1998).

## Scope for future work

- The present work has used sample CAD models for its studies CAD models of injection molding parts from a real industry and the optimisation frame work developed in the present work for process parameter optimisation should be combined and tested more extensively
- In this study we have used a second regression models One may go for the higher order models for the better results
- In this study we have done bi-objective optimisation of the injection molding process parameters One may do the multi-optimisation of the injection molding process parameters
- In our study we were not able to evaluate the effect of NSGA parameters like  $\sigma_{share}$  on the distribution of population on different fronts This points towards the scope for a detail study of NSGA parameters
- The quality of the injection molded part is affected by the mold design and cooling system design apart from the process conditions. Therefore, one may go for the optimisation of the parameters of injection molded design and cooling system design using GA.
- An enhanced multi-objective GA (ENGA) (Srinivas, 1998) which is proved to be faster in convergence than NSGA, ENGA can be used for the multi-objective optimisation

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